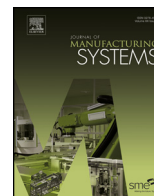




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Technical Paper

A case-oriented approach to a lead/acid battery closed-loop supply chain network design under risk and uncertainty

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ABSTRACT

A new scenario based stochastic and possibilistic mixed integer programming model for a multi-objective closed-loop supply chain network design problem by considering financial and collection risks is proposed. Uncertainties in the form of randomness and fuzziness are handled together for a better reflection of the problem. Different risk measures such as “variability index”, “downside risk” and “conditional value at risk” are integrated within the proposed model. Particularly, for the downside risk measure, target/threshold values are considered as fuzzy and described by their own possibility distribution. The proposed hybrid model is applied to an illustrative example inspired by the lead/acid industry in Turkey. Computational results of applying the different risk measures suggest that using downside risk model with fuzzy targets is found to be an appropriate choice for the stated closed-loop supply chain network design problem in terms of “computational efficiency”, “handling uncertainty” and “solution quality”

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1. Introduction

Recently, there is a great deal of interest in risk management issues by both researchers and practitioners in the scope of supply chain (SC) management. It is emphasized by You et al. [1] that in addition to cost reduction and profit maximization, managing the risks along the SCs has drawn significant attention due to the competition in the global marketplace. Due to the global competition, technological change and continual search for competitive advantage, SC risk management has been an attractive topic. In SC risk management, coordination and collaboration of processes and activities across functions within a network of organizations are generally handled [2]. According to Wang and Hsu [3], the uncertainty embedded in Reverse Logistics (RL) and Closed-Loop Supply Chains (CLSC) has been a challenge for green supply chain concept. Because, the uncertain factors of the reverse flows are more complex than the forward part of the supply chain. Apart from the uncertain demand, the values of recovery rate and disposal rate pose difficulties in estimation and constitute the major factors of the CLSC management. Indeed, inaccurate forecasting of these parameters causes increases in various types of financial risks and

also the risks related to the collection and recovery amounts. Thus, risk management has an important role in controlling the uncertainty level in optimization problems. It is highlighted by Azaron et al. [4] that minimization of the risk reflected by the variance of the total cost namely financial risk has not been considered in the existing comprehensive SC network design models sufficiently. Babazadeh et al. [5] also supported this viewpoint by denoting the lack of SC, RL and CLSC network design models which able to measure and control the risk resulted from the dynamic and uncertain nature of the problem. Additionally, all of the quantitative risk management models in these network design problems focus only on the financial risk issues as a result of the considered objective function (minimize total cost and/or maximize overall profit). On the other hand, strict legal obligations and the environmental awareness put the screws on enterprises for collection and recovery of used scrap products as much as possible. Therefore, the risk of non-collecting the end-of-life products up to the predetermined target value emerges as an important issue in CLSC management and RL environment. For these reasons, the risk of end-of-life product collection should also be modeled quantitatively besides the financial risks. In this context, collection risk can be defined as the “probability of not collecting the used products up to a certain level or target defined by the environmental laws”.

Before applying different risk management models to a SC, CLSC or RL network design models, uncertainties related to the studied problem should be taken into account effectively as risks mostly

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take root from the uncertainties. In other words, main sources of the risks are related to uncertainties in the stated problem. However, most of the real life applications involve different uncertainty types (randomness, fuzziness and dynamism) altogether. On the other hand, the majority of the papers in the literature deal with these uncertainty categories separately. In fact, these uncertainty types should be taken into account simultaneously. Therefore, this study presents a hybrid multi-scenario based stochastic and possibilistic programming approach to a lead/acid battery CLSC network design problem where stochastic parameters have randomness in nature and possibilistic parameters are represented by triangular fuzzy numbers.

Briefly, the main purpose of this study is to develop a new multi-objective CLSC network design model for a lead/acid battery industry considering risk measures both financial and collection objectives simultaneously. Another important aim of this research is to be able to handle different uncertainty types such as randomness, fuzziness, etc. altogether in the same problem since it can better reflect the real-life cases. Moreover, utilized target/threshold values should be taken as fuzzy data because of the lack of some information and uncertainty while formulating the downside risk metric. To the best of our knowledge, this paper constitutes the first research considering the mentioned targets including uncertainty. At the end of the study, all of the utilized risk management models for the stated CLSC network design problem under uncertainty are compared.

The rest of the paper is organized as follows: In Section 2, the relevant literature on RL and CLSC network design problem under uncertainty and the risk management models for SC, RL and CLSC planning problems are given. In Section 3, details of the problem with the model formulation, assumptions and model parameters are described. Transformation of the hybrid model into the equivalent auxiliary crisp & stochastic form is also given in the same section. In Section 4, application of the proposed model to an illustrative example inspired by Turkey case is discussed. Adaption and comparison of the previously mentioned risk management metrics into the proposed hybrid model is also given in Section 5. In Section 6, concluding remarks and suggestions for future research directions are presented.

2. Literature review on SC, CLSC & RL network design under uncertainty and risk

Uncertainty is one of the main attentions in CLSC management due to the demand, land filling and recovery rates which are the three important factors contributed to the uncertainty [3]. In other words, uncertainty in timing, quality and quantity of product returns are important aspects of RL and CLSC network design problems. However, development of dynamic, probabilistic and stochastic SC and production-distribution planning models is still investigated by relatively few researchers [6]. In addition, they expressed the development of these types of models as the future research trends. Wang and Hsu [3] also highlighted that appropriate models which aim to handle the uncertainty in CLSCs is still lacking. As mentioned by Ilgin and Gupta [7], this uncertainty issue can be handled by using robust optimization techniques in stochastic RL network design models. Additionally, fuzzy mathematical programming can also be used since the deterministic models assume certainty in all aspects of the problem although some of the parameters cannot be precisely set like capacities and target for objective function achievement [8]. The articles handling uncertainty issue and discussing related methodologies can be summarized as follows: Salema et al. [9] reformulated the generic RL network design model while taking into account the production/storage capacities

of opened facilities, multiple product production and uncertainty related to the amounts of customers' demand and product returns by employing multiple-scenario based approach. A multi-echelon CLSC inventory model is proposed by Chung et al. [10] in order to obtain optimal inventory policy for maximizing the joint profits of the supplier, manufacturer, third-party recycle dealer and retailer. Pishvaei et al. [11] developed a stochastic programming model for a CLSC network design by using scenario-based stochastic approach. In that paper demands, the quantity and the quality of returns and the variable costs were considered as uncertain parameters. A two-stage stochastic programming model was proposed by Kara and Onut [12] for single product, two-echelon capacitated RL network design in waste paper recycling industry in order to maximize revenue. Demand and amounts of collected products were assumed to be uncertain and fitted to the normal distribution while generating alternative scenarios. El-Sayed et al. [13] developed a multi-period, multi-echelon and multi-stage stochastic program for an integrated forward-reverse logistics network design while assuming the demands of customer zones to be stochastic. Lee et al. [14] also proposed a two-stage stochastic programming model for sustainable logistics network design. Demands of forward products and the supply of returned products are assumed to be stochastic parameters which have known distributions. Uncertain demands, returns, delivery times, costs and capacities were taken into account by using possibilistic programming approach in Pishvaei and Torabi [15] for a CLSC network design problem which integrates strategic and tactical planning decisions. Because of the some disadvantages of the stochastic programming such as difficulty related to availability of historical data and complex modeling, uncertain demand and purchasing cost in strategic agile CLSC network design problem of perishable goods was handled via interval robust optimization technique by Hasani et al. [16]. Uncertainties in demand and yield rate are modeled by Qiang et al. [17] for a CLSC network with decentralized decision makers that consist of raw material suppliers, retailers and manufacturers. Subulan et al. [18] developed a fuzzy mixed integer programming model with non-linear constraints for medium-term planning in a CLSC with remanufacturing option. In their proposed model, storage capacities, retailers' and wholesalers' demands, return rates, acceptance ratios, weekly available production/remanufacturing times, transportation upper bounds and objective function value are considered as fuzzy. A fuzzy rule-based system for performance evaluation of a CLSC was also developed by Olugu and Wong [19] in automotive industry. Pishvaei and Razmi [20] developed a multi-objective possibilistic mixed integer programming model for an environmental supply chain network design. They used possibilistic programming approach for handling the imprecise parameters such as lower cost items, demands, return quantities and the facilities' capacities.

Apart from the existing literature, this study presents a hybrid of stochastic & possibilistic mixed integer programming model for a CLSC network design problem since the real life applications involve different types of uncertainties altogether. On the other hand, greater amount of papers in the literature deal with these uncertainty categories separately as mentioned above. In the proposed model, multi-scenario based stochastic programming approach and possibilistic programming are utilized simultaneously. Demands, return rates and quality of the returned products are considered as stochastic parameters since they have randomness in nature. Furthermore, because they may have epistemic uncertainty (unavailability or incompleteness of the historical data, insufficient data, etc.) all of the cost parameters, recycling rates, maximum number of opened facilities, maximum allowable distances for distribution and collection are considered as possibilistic parameters and described by possibility distributions.

Table 1
Risk management models for SC, CLSC and RL network design.

Article	Prob. Type	Risk measures					
		Variance	Variability index	Probabilistic financial risk	Downside risk (Deterministic)	Downside risk (Fuzzy)	CVaR
Shah [23]	SC				✓		
Barbaro et al. [24]	CP			✓	✓		
Guillen et al. [21]	SC			✓	✓		
Azaron et al. [4]	SC	✓		✓			
You et al. [1]	SC	✓	✓	✓	✓		
El-Sayed et al. [13]	CLSC						
Gebreslassie et al. [25]	SC				✓		✓
Nickel et al. [26]	SC				✓		
Babazadeh et al. [5]	CLSC						✓
Ramezani et al. [27]	CLSC			✓			
Our Article	CLSC		✓		✓	✓	✓

CP: Capacity planning

In the scope of risk management models in SC, CLSC and RL network design concepts, most commonly used risk measures are explained by You et al. [1] as follows:

- I. managing the variance,
- II. managing the variability index,
- III. managing the probabilistic financial risk, and finally
- IV. managing the downside risk.

Different from the above risk measures, Conditional Value at Risk (CVaR) criterion which was proposed by Rockafellar and Uryasev [21] was used by Babazadeh et al. [5] in order to measure the investment risk and control the risk level of their CLSC planning model. In this study, variance management model is not applied since the objective function includes non-linear terms which make large scaled problems very difficult to be solved optimally. Therefore, as an alternative to variance measure, variability index model is used in order to obtain low variance in a more effective manner. In addition, it is also emphasized by You et al. [1] that variance management model is not an effective tool in reducing the high cost risk, only lead to less variance, or in other words, reducing the probability of lower cost. A similar circumstance is also valid for probabilistic financial risk measure. As mentioned by [1,22], downside risk can be used instead of probabilistic financial risk because of avoiding the use of binary variables for each scenario which will increase the size of the model. This makes the problem's size very large as the number of scenarios increases. As a result, downside risk is used in this paper instead of probabilistic financial risk metric. As reported in [1,22], downside risk management model is the most effective tool or the best choice among the others since its computational efficiency. Available literature that uses the above risk measures in SC, CLSC and RL network design concept can be summarized as in Table 1.

In this study, following contributions are made by developing a new case-oriented mathematical programming approach for a lead/acid battery closed-loop supply chain network design problem under risk and uncertainty: (I) A novel hybrid scenario based stochastic & possibilistic programming model is proposed for Turkish lead/acid battery industry while taking into account different uncertainty types such as randomness, fuzziness, etc. simultaneously. (II) In the proposed model, real life decision making situations in the lead/acid battery sector related to the purchasing and/or selling of end-of-life batteries to the scrap dealers are also considered. Moreover, decision related to the types of the facilities such as distribution, collection or hybrid that will be opened is as

important as where they will be located in the examined sector. Therefore, in addition to determine the facility locations, facility type is also handled in the developed model for the candidate locations. (III) In contrast to the existing risk management models in the literature, this paper does not focus only the financial risk issues but also the risk of non-collecting end-of-life products up to a predetermined target value. In other words, collection risks of used batteries are also considered besides the financial risks in an integrated manner. (IV) In most of the risk management metrics, target values of the objectives related to the risk issues were determined as certain parameters by the decision maker(s). However, specification of this value in a definite way is a challenging task since including some sort of ambiguity. For this reason, this paper deals with imprecise target values which are represented by triangular fuzzy numbers under uncertain environments.

3. Problem definition and hybrid model formulation

Lead/acid battery industry requires an optimal design for the CLSC network. In this study, not only “opening of regional wholesalers for forward flows of newly produced batteries” and “the setting up of the collection centers for reverse flows”, but also “a hybrid facility which undertake the transfer of both forward and returned batteries” are taken into account (see in Fig. 1) as in the model developed by Lee et al. [14]. In the forward supply chain, in addition to provide some materials from the recycling way, the main components of a lead acid battery are purchased from different vendors for new battery production. Once the battery is produced in different new battery manufacturers it has to be distributed via regional wholesalers or hybrid facilities to the dealers or retailers. In the reverse chain, the end user leaves the spent battery at the retailer where it is replaced by a new one at the end of battery use. Then the collected spent batteries are transported to the licensed recycling facilities through collection centers or hybrid facilities.

Used batteries are controlled in terms of quality specifications for recycling process. The useless batteries are disposed off and the appropriate batteries for recycling are shipped to the licensed recycling facilities which are secondary lead smelters and plastic recyclers. In accordance with the need for spent battery, additional used batteries can be purchased from the scrap dealers or conversely sales to the excessive batteries to scrap dealers can be performed. The model assumptions utilized in developing the mathematical program can be stated as follows:

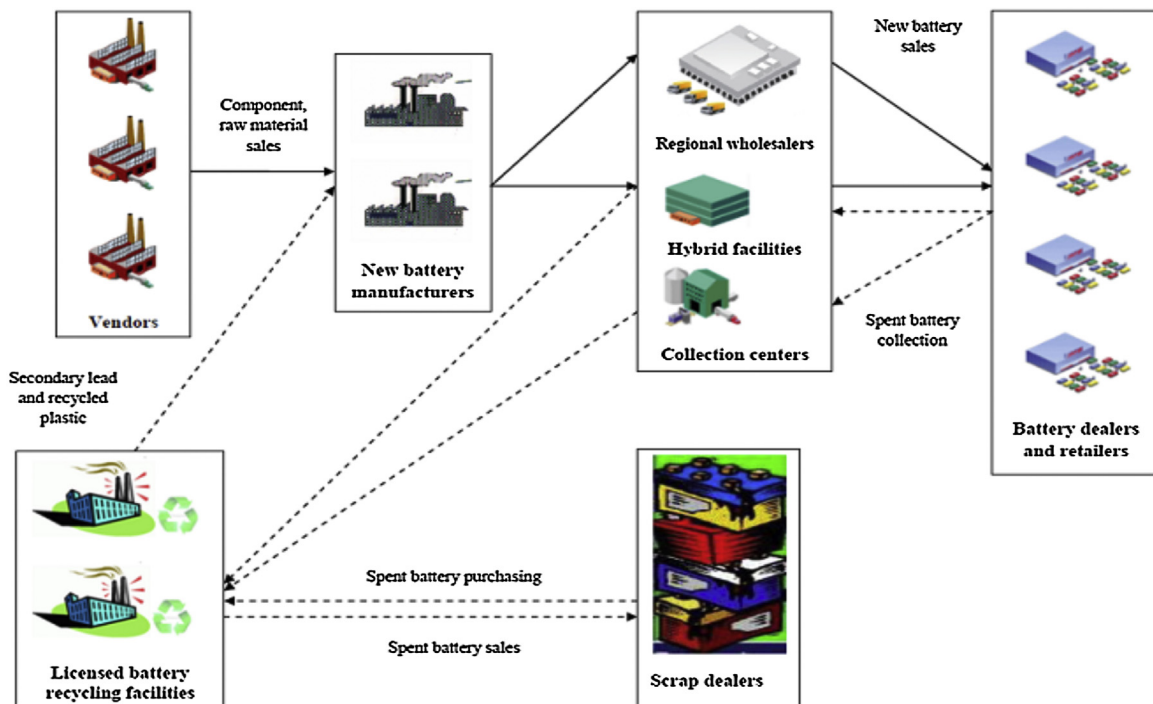


Fig. 1. Closed-loop supply chain network representation for lead/acid battery recovery.

- There are two different options for the new battery manufacturers to supply components such as lead, plastic, etc. One is purchasing them from different suppliers; and the other one is acquiring them by recycling from the licensed recycling facilities.
- Shortages and inventory holding are not allowed and cost parameters at all stages of the CLSC network do not change. Transportation lead times between the stages are not taken into account because of the single period consideration.
- The dealers' or retailers' demand forecasts, return rate for the used batteries and the disposal fraction are not exactly known and considered as stochastic parameters. Quantity of returned batteries from a given dealer or retailer is the fraction of the total demand of that dealer or retailer.
- Any collection center or hybrid facility can purchase additional scrap batteries from the scrap dealers for recycling in the case of need. Furthermore, this collection center or hybrid facility can also sell a certain amount of their collected scrap batteries to the scrap dealers if it has a cost advantage. However, purchasing and selling operation for the same type of scrap battery cannot be performed simultaneously and at most one alternative can be done. On the other hand, these operations (purchases and sales) can be performed at the same time for different types of scrap batteries by the collection center or hybrid facility.
- It is assumed that physical locations of scrap dealers have no impact on the CLSC network design and they have an infinite capacity and budget for used battery sales or purchasing.

3.1. A hybrid scenario based stochastic and possibilistic MILP formulation of the problem

The uncertainty in data can be categorized into two groups: (i) randomness and (ii) epistemic uncertainty. In general, stochastic

programming and possibilistic approaches were used for handling these types of uncertainties [20,28]. The main sources of epistemic uncertainty are the unavailability or incompleteness of the historical data (insufficient data). Epistemic uncertainty deals with the ill-known parameters which have their own possibility distribution. Thus, using probability distributions as in the stochastic optimization becomes impossible. In this situation, possibility distributions should be forecasted based on the decision makers' experiences or knowledge [20]. In this study, all of the cost parameters as well as selling prices of different kinds of lead/acid batteries, maximum number of opened collection centers and hybrid facilities, recycling rates, maximum allowable distances for new battery distribution and used battery collection are considered as ill-known parameters and represented by fuzzy triangular numbers which are described by possibility distributions. However, other uncertainty factors such as "demands of the dealers", "return fractions for the end-of-life batteries" and "the disposal rates" which constitute the dynamics of RL and CLSC management are considered as stochastic parameters. Therefore, the proposed hybrid mathematical model takes into account the deterministic, stochastic and possibilistic parameters in an integrated manner. For better understanding of the proposed hybrid multi-scenario based stochastic and possibilistic model, the compact form of the MILP formulation is shown in Appendix I. Because of satisfying the demand and return requirements of battery dealers in each scenario and avoiding the infeasibility problem, the locations and numbers of facilities cannot be changed [11]. Therefore, scenario index s should not be added to the facility opening decisions such as w_j , c_j and h_j . According to the above explanations, a multi-objective, multi-echelon, multi-product hybrid stochastic & possibilistic CLSC network design model can be given through the following equations by using the indices, parameters and decision variables which are defined in Appendix II. The first objective function of the hybrid MILP model is to minimize the total expected CLSC cost which involves imprecise cost parameters.

$$\begin{aligned}
 E[\text{Total CLSC Cost}] = & \sum_{j \in J} \tilde{f}1_j \cdot w_j + \sum_{j \in J} \tilde{f}2_j \cdot c_j + \sum_{j \in J} \tilde{f}3_j \cdot h_j + \sum_{l \in L} \tilde{f}4_l \cdot r_l + \sum_{b \in B} \sum_{i \in I} \sum_{s \in S} \pi_s \cdot Q_{bis} \cdot \widetilde{PRC}_b \\
 & + \sum_{b \in B} \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \sum_{s \in S} \pi_s \cdot x_{bijks} \cdot \widetilde{TC}_b \cdot (d1_{ij} + d2_{jk}) + \sum_{b \in B} \sum_{k \in K} \sum_{j \in J} \sum_{l \in L} \sum_{s \in S} \pi_s \cdot x1_{bkjls} \cdot \widetilde{TC}_{1b} \cdot (d2_{jk} + d3_{jl}) \\
 & + \sum_{b \in B} \sum_{i \in I} \sum_{l \in L} \sum_{s \in S} \pi_s \cdot q_{bjls} \cdot \widetilde{TC}_{1b} \cdot d3_{jl} + \sum_{c \in C} \sum_{l \in L} \sum_{i \in I} \sum_{s \in S} \pi_s \cdot x2_{clis} \cdot \widetilde{TC}_c \cdot d4_{li} + \sum_{c \in C} \sum_{v \in V} \sum_{i \in I} \sum_{s \in S} \pi_s \cdot QP_{cv is} \cdot \widetilde{PUC}_{cvi} \\
 & + \sum_{b \in B} \sum_{j \in J} \sum_{l \in L} \sum_{s \in S} \pi_s \cdot q_{bjls} \cdot \widetilde{PC}_{bj} + \sum_{b \in B} \sum_{l \in L} \sum_{s \in S} \pi_s \cdot RE_{b ls} \cdot \widetilde{RC}_{bl} + \sum_{b \in B} \sum_{j \in J} \sum_{k \in K} \sum_{s \in S} \pi_s \cdot y1_{kjs} \cdot DE_{bks} S_{bs} \cdot \widetilde{CC}_b \\
 & + \sum_{b \in B} \sum_{k \in K} \sum_{j \in J} \sum_{l \in L} \sum_{s \in S} \pi_s \cdot (x1_{bkjls} + q_{bjls} - q1_{bjs}) \cdot \theta_{bs} \cdot \widetilde{DIC}_b - \sum_{b \in B} \sum_{j \in J} \sum_{s \in S} \pi_s \cdot q1_{bjs} \cdot \widetilde{SP}_{bj}
 \end{aligned} \quad (1)$$

The second objective function is to maximize the total expected collection coverage. In other words, maximization of the coverage of collected batteries through opened collection centers and/or hybrid facilities is aimed with this goal. Formulation of this goal is motivated based on the well known problem in the literature as “maximal coverage problem”. Maximal coverage location problem (MCLP) is defined by Davari et al. [29] as investigating the location of a number of facilities on a network in order to maximize the covered population. For covering a population, at least one facility must be opened within a pre-defined distance of it. To the best of our knowledge, this objective has not been addressed by the previous works so far and is very vital in the case of scarce financial resources.

$$E[\text{Total Collection Coverage}] = \sum_{b \in B} \sum_{k \in K} \sum_{j \in J} \sum_{s \in S} \pi_s \cdot DE_{bks} \cdot S_{bs} \cdot y1_{kjs} \quad (2)$$

Constraints are expressed by Eqs. (3)–(26).

$$\sum_{j \in J} c_j + h_j \leq \tilde{N} \quad \forall s \quad (3)$$

$$y1_{kjs} \leq \alpha_{jk} \cdot (c_j + h_j) \quad \forall s, \forall j, \forall k \quad (4)$$

$$\sum_{k \in K} y_{jks} \leq M \cdot (h_j + w_j) \quad \forall s, \forall j \quad (5)$$

$$\sum_{j \in J} y1_{kjs} \leq 1 \quad \forall s, \forall k \quad (6)$$

$$\sum_{j \in J} y_{jks} = 1 \quad \forall s, \forall k \quad (7)$$

$$\sum_{k \in K} y_{jks} \cdot DE_{bks} \leq cap_{bj}^f \cdot w_j + hcap_{bj}^f \cdot h_j \quad \forall s, \forall b, \forall j \quad (8)$$

$$\sum_{i \in I} x_{bijks} = DE_{bks} \cdot y_{jks} \quad \forall s, \forall b, \forall k, \forall j \quad (9)$$

$$\sum_{k \in K} y1_{kjs} \cdot DE_{bks} \cdot S_{bs} + \sum_{l \in L} q_{bjls} - q1_{bjs} \leq cap_{bj}^r \cdot c_j \quad (10)$$

$$+ hcap_{bj}^r \cdot h_j \quad \forall s, \forall b, \forall j$$

$$\sum_{l \in L} x1_{bkjls} = y1_{kjs} \cdot DE_{bks} \cdot S_{bs} \quad \forall s, \forall b, \forall k, \forall j \quad (11)$$

$$w_j + c_j + h_j \leq 1 \quad \forall s, \forall j \quad (12)$$

$$\sum_{j \in J} \sum_{k \in K} x_{bijks} \leq Q_{bis} \quad \forall s, \forall b, \forall i \quad (13)$$

$$Q_{bis} \leq Prcap_{bi} \quad \forall s, \forall b, \forall i \quad (14)$$

$$\left\{ \sum_{k \in K} \sum_{j \in J} x1_{bkjls} + \sum_{k \in K} q_{bjls} - \sum_{k \in K} q1_{bjs} \right\} \cdot (1 - \theta_{bs}) \cdot W_b = RE_{b ls} \quad \forall s, \forall b, \forall l \quad (15)$$

$$\sum_{i \in I} x2_{clis} = \sum_{b \in B} RE_{b ls} \cdot \bar{\gamma}_b \cdot \varepsilon_{cb} \quad \forall s, \forall c, \forall l \quad (16)$$

$$\sum_{l \in L} q_{bjls} \leq M \cdot y_{bjs} \quad \forall s, \forall b, \forall j \quad (17)$$

$$q1_{bjs} \leq M \cdot y1_{bjs} \quad \forall s, \forall b, \forall j \quad (18)$$

$$y_{bjs} + y1_{bjs} \leq 1 \quad \forall s, \forall b, \forall j \quad (19)$$

$$d2_{jk} \cdot y_{jks} \leq \widetilde{DMAX} \quad \forall s, \forall j, \forall k \quad (20)$$

$$d2_{jk} \cdot y1_{kjs} \leq \widetilde{D1MAX} \quad \forall s, \forall j, \forall k \quad (21)$$

$$\sum_{v \in V} QP_{cv is} + \sum_{l \in L} x2_{clis} = \sum_{b \in B} Q_{bis} \cdot \rho_{cb} \quad \forall s, \forall c, \forall i \quad (22)$$

$$RE_{b ls} \leq REcap_{bl} \cdot r_l \quad \forall s, \forall b, \forall l \quad (23)$$

$$x1_{bkjls} + q_{bjls} \leq M \cdot r_l \quad \forall s, \forall b, \forall k, \forall j, \forall l \quad (24)$$

$$\sum_{l \in L} QP_{cv is} \leq Vcap_{cv} \quad \forall s, \forall c, \forall v \quad (25)$$

$$w_j, c_j, h_j, r_l, y_{jks}, y1_{kjs}, y_{bjs}, y1_{bjs} \in (0, 1) \quad (26)$$

All other variables are continuous and positive

Constraint (3) limits the number of collection centers or hybrid facilities to be opened for spent battery returns in each scenario. Constraint (4) determines which battery returns are covered within the acceptable service distance. Service means collection of used batteries from the retailers/dealers. If no collection center or hybrid facility is located in the scenario s , the right hand side of that constraint will be zero and forces $y1_{kjs}$ to be equal to zero. According to the constraint (5) if a regional wholesaler or hybrid facility is opened, it may serves to any dealer or retailer. In other words, there may be an outgoing flow (distribution operation) from this depot to the dealers. Constraint (6) assures that a battery dealer may be assigned to at most a single collection center or hybrid facility for spent battery returns for each scenario. Since these assignments may be impossible because of the logic of maximal covering problem, ≤ 1 is used in that constraint set. Constraint (7) assures that a battery dealer is assigned to a single regional wholesaler or hybrid facility for forward flow of newly produced batteries. In other words, demands of the battery dealers must be satisfied by a single regional wholesaler or hybrid facility. Constraint (8) limits the

number of newly produced batteries shipped through the regional wholesaler or hybrid facility to its capacity of performing forward flows. Constraint (9) maintains that the demands of battery dealers' for newly produced batteries must be satisfied in each scenario. Constraint (10) restricts the number of returned batteries transferred through a collection center or hybrid facility to its capacity of performing reverse flows. Constraint (11) ensures that volume of returned batteries from a given dealer or retailer is the fraction of total demand of that dealer or retailer. Constraint (12) ensures that at most one type of facility (regional wholesaler, collection center or hybrid facility) can be opened at the potential depot locations in scenario s . Constraint (13) guarantees that the outgoing flows from a new battery manufacturer cannot exceed the production quantity at that manufacturer. Constraint (14) ensures that the production quantity of each battery type must not get over the production capacity of the new battery manufacturers. According to constraint (15), one can calculate the quantity of used batteries in weight that are recyclable. Constraint (16) is the conservation of flow constraint for the licensed recycling facilities. Constraint (17) and (18) provide that the variables related to quantities must take value in the case of used battery purchasing from the scrap dealers or sales of used batteries to the scrap dealers. Constraint (19) ensures that purchasing and selling operations for the same type of scrap batteries cannot be actualized simultaneously (in that single time period). At most one of these variables can take a value for each battery type, scenario and each collection center or hybrid facility. Constraints (20) and (21) assure that each regional wholesaler, collection center or hybrid facility should be located within acceptable proximity of battery dealers over scenario s . Constraint (22) is balance equation for the components that are used in the new battery production. Constraints (23) and (25) are capacity constraints for the licensed recycling facilities and vendors, respectively. Constraint (24) makes sure that if a licensed recycling facility is opened at the candidate location, there may be incoming flows of used batteries from the collection centers, hybrid facilities or scrap dealers to this recycling facility. Constraint (26) represents the binary variables such as opening decisions for the facilities; assignment decisions for allocating battery dealers to the regional wholesalers, collection centers and hybrid facilities and decisions regarding scrap battery purchasing or sales.

3.2. Transformation of the hybrid model into equivalent auxiliary crisp and stochastic form

In order to transform developed hybrid model into equivalent crisp and stochastic form, the method for solving fuzzy linear programming models which was proposed by Jimenez et al. [30] is utilized. This method mainly depends on the "expected interval", "expected value" of fuzzy numbers and as well as fuzzy ranking method of Jimenez [31]. The most important reason for choosing this technique is that one can achieve in a computationally efficient way of solving this possibilistic programming problems with its linearity and without any increments in objective functions and inequality constraints [20]. On the other hand, it is required one more constraint in the case of equality constraints [15,32]. Eqs. (1), (3), (16), (20) and (21) which involve possibilistic parameters are converted and the non-possibilistic constraints with the second goal are added to the model and remaining unalterable. The equivalent crisp α -parametric linear program including stochastic terms is given in Appendix III.

4. Computational case study

In order to see the performance of the proposed hybrid stochastic & possibilistic multi-objective linear programming (HMOLP)

Table 2
Nominal data for deterministic model.

Parameters	Range of values
Demand forecasts of battery dealers (units)	Uniform distribution (500, 2500)
Unit production cost (\$/unit)	25–65
Unit transportation cost for newly produced batteries (\$/km unit)	0.001–0.003
Unit transportation cost for used batteries (\$/km unit)	0.002–0.004
Unit transportation cost for materials/components (\$/kg unit)	0.008–0.015
Recycling cost (\$/kg)	0.47–1.0
Unit collection cost (\$/unit)	2–5
Unit disposal cost (\$/unit)	1–3
Unit purchasing cost of used batteries from scrap dealers (\$/unit)	5–14
Unit selling price of used batteries to scrap dealers (\$/unit)	5–14
Unit purchasing cost for materials/components from the vendors (\$/kg)	0.5–4
Maximum number of opened collection centers and hybrid facilities	5
Fixed cost of opening regional wholesaler (\$)	150,000–230,000
Fixed cost of opening collection centers (\$)	60,000–120,000
Fixed cost of opening hybrid facilities (\$)	230,000–390,000
Fixed cost of opening licensed recycling facilities (\$)	400,000–600,000
Production capacity of battery manufacturers (units)	28,000–56,000
Capacity of regional wholesalers (units)	7500–15,000
Capacity of collection centers (units)	10,000–20,000
Capacity of hybrid facilities for forward flows (units)	5250–10,500
Capacity of hybrid facilities for reverse flows (units)	7000–14,000
Capacity of licensed recycling facilities (kg.)	750,000–4,550,000
Capacity of vendors (units)	50,000–90,000
Return fraction	50%
Disposal rate	5%
Recycling rate	70–80%
Weight of used batteries (kg./unit)	15–35
Contribution percentages of materials/components	10–55%
Distances (km)	0–1650
Max. acceptable distances (km)	400–500

model, an illustrative example is generated as in Fig. 2 based on inspiration from a lead/acid battery CLSC in Turkey.

In the computational case study, there are three types of batteries, three types of components, two new battery manufacturers, three vendors to supply components/raw materials, thirty dealers or retailers with uniformly distributed yearly demands, thirteen potential sites for collection, distribution or both activities as hybrid facilities, four alternatives for licensed recycling facilities and finally twenty seven scenarios. In the solution phase of the problem, the proposed model is first solved with nominal data where all of the parameters are deterministic (see in Table 2). Discrete numbers of scenarios are generated with probabilities for the stochastic parameters as it can be seen in Fig. 3 where the scenario #13 which has the greatest probability represents the deterministic model with nominal data. As it can be clearly understood, scenario index s is not required in the deterministic model.

In addition, all possibilistic parameters are assumed to have most likely values of the defined possibility distributions. When the model is run under this nominal data through optimization software GAMS Rev 140 including CPLEX 9.0 product on an Intel Core i7 2 GHz IBM PC for each objective function independently, computational results are obtained as in Table 3 for the deterministic model.

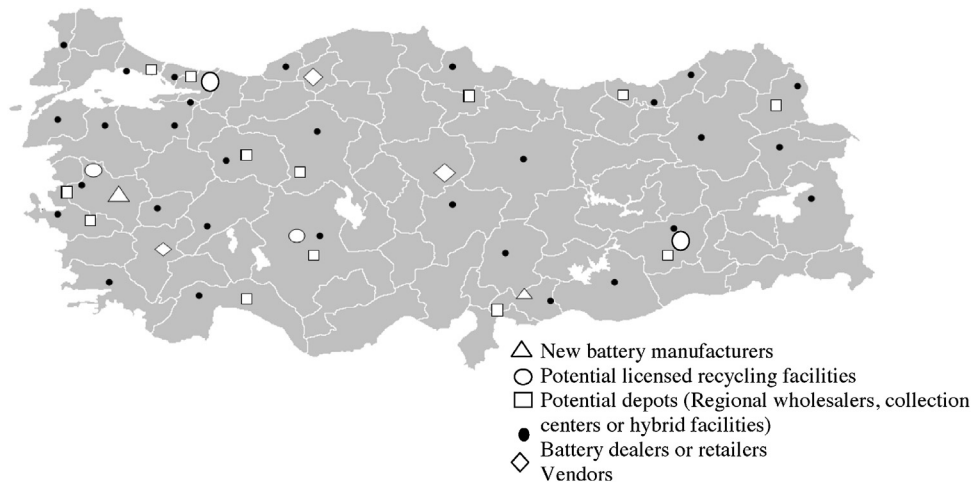


Fig. 2. Configuration of the computational case study.

Moreover, corresponding optimal CLSC configurations for each objective are represented in Figs. 4 and 5. These networks reveal that the objectives constitute a conflict while designing the CLSC. In later, in the stochastic optimization model, possibilistic parameters are not included and assumed to have most likely values of the defined possibility distributions again.

Before solving this stochastic optimization model, each scenario is run deterministically and the results are depicted in Table 4 for each objective function.

Afterwards, stochastic optimization model is run and the results are given in Table 5. The obtained solution is not optimal for all of the individual scenarios. The occurrence probability that is assigned to each scenario displays the importance of that scenario under uncertain environment.

In the stochastic optimization model, one more collection center will be opened by considering only the first objective function. On the other hand, additional two hybrid facilities will be opened in place of the collection centers in the stochastic optimization

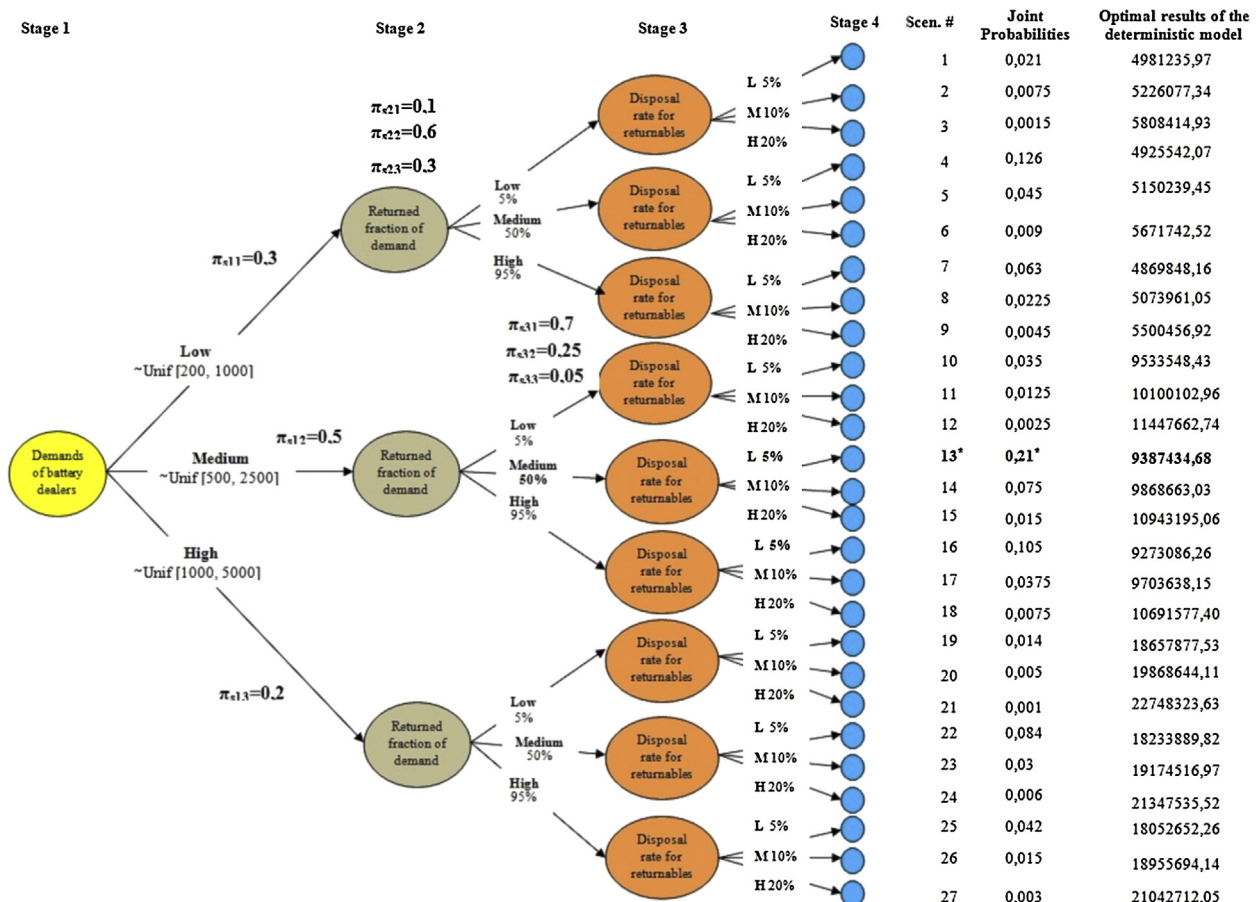


Fig. 3. Scenario tree generation.

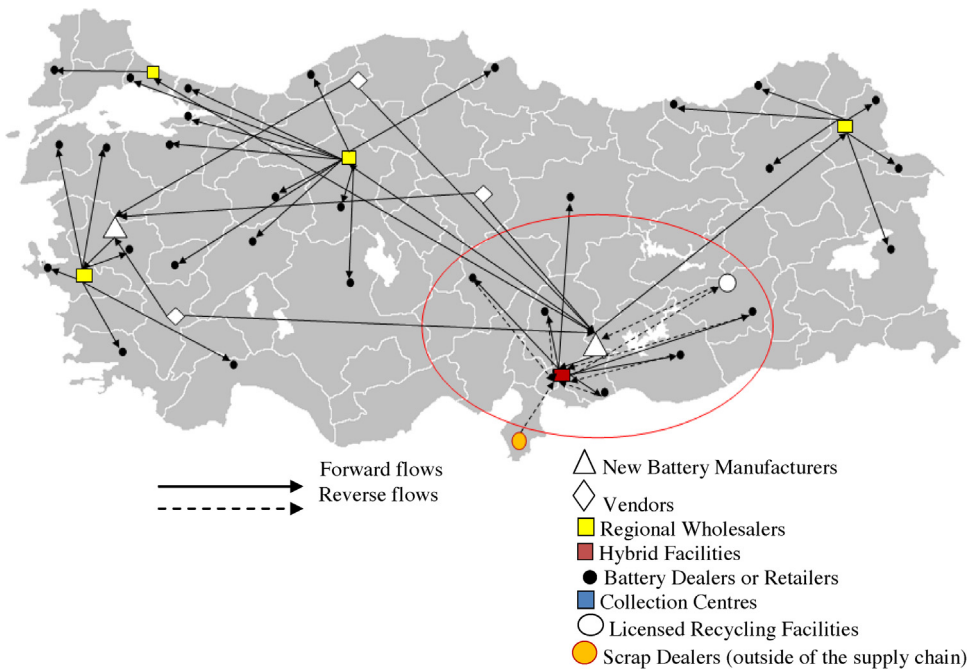


Fig. 4. Optimal CLSC configuration under nominal data for deterministic model considering only total cost.

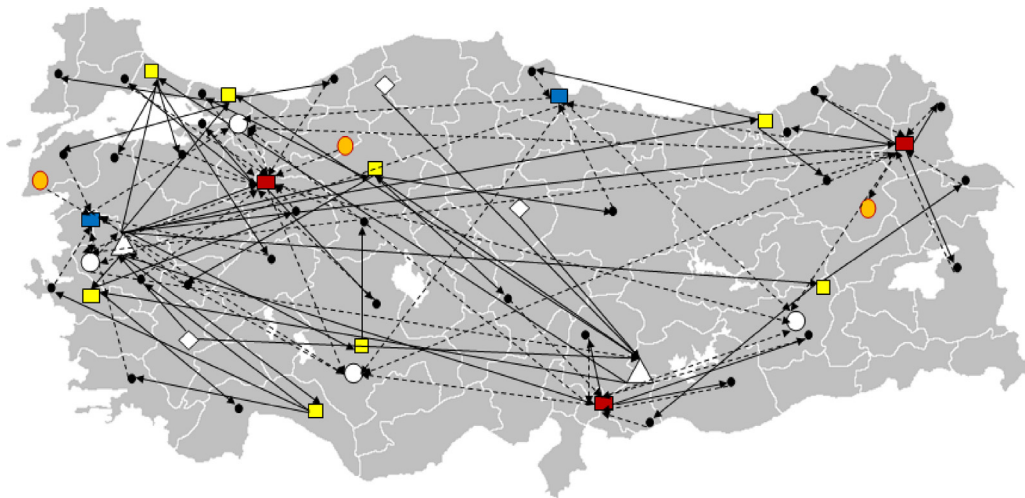


Fig. 5. Optimal CLSC configuration under nominal data considering only total collection coverage.

Table 3
Computational results under nominal data.

	Total CLSC cost (Objective 1)	Total collection coverage (Objective 2)
Total number of variables	8177	8178
Total number of binary variables	901	901
Total number of constraints	8535	8537
Total number of iterations	6162	1128
Total cost of the CLSC	\$11,026,286.0455	\$16,407,000
Total collection coverage	10,754 units	61,564.5
CPU time (s)	0.125	0.124
Number of opened regional wholesalers	4	8
Number of opened collection centers	–	2
Number of opened hybrid facilities	1	3
Number of opened licensed recycling facilities	1	4

model when the second goal is optimized. When the performance of the stochastic optimization model for each objective under each scenario is analyzed, both cost and collection coverage will also increase in case of demand increments of the battery dealers. Although the return fraction has a significant impact on the collection coverage, it has nearly no severe effect on the cost objective. Moreover, escalation in the disposal rate will cause cost increments and has no impact on the collection coverage as an expected result.

After solving the stochastic optimization model, possibilistic parameters are also taken into account in the hybrid model. Data related to these possibilistic parameters are given in Tables 6 and 7. Before solving this hybrid model, it is converted into the equivalent crisp and stochastic form as mentioned before.

Computational results of the hybrid model according to the different minimum acceptable feasibility degrees (α -levels) are given in Table 8. As it can be seen from Table 8, the values of both objective functions deteriorate when the minimum acceptable feasibility degree is increased. The main reason of the decreases in collection

Table 4
Computational results under scenarios for deterministic model.

Scenario #	Total CLSC cost (Objective 1) (\$)	Total collection coverage (Objective 2) (units)	# of opened regional wholesalers (Obj ₁ /Obj ₂)	# of opened collection centers (Obj ₁ /Obj ₂)	# of opened hybrid facilities (Obj ₁ /Obj ₂)	# of opened licensed recycling facilities (Obj ₁ /Obj ₂)
1	5,605,851.585	2646.2	4/8	NA/2	1/3	1/4
2	5,773,835.127	2646.2	4/8	NA/2	1/3	1/4
3	6,173,212.628	2646.2	4/8	NA/2	1/3	1/4
4	5,585,397.234	26,462	4/8	NA/NA	1/5	1/4
5	5,743,382.661	26,462	4/8	NA/NA	1/5	1/4
6	6,118,720.305	26,462	4/8	NA/NA	1/5	1/4
7	5,564,942.883	50,277.8	4/8	NA/1	1/4	1/4
8	5,712,930.195	50,277.8	4/8	NA/1	1/4	1/4
9	5,975,109.207	50,277.8	3/8	1/1	2/4	1/4
10	11,417,914.729	6156.45	4/8	NA/2	1/3	1/4
11	11,886,773.254	6156.45	4/8	NA/1	1/4	1/4
12	13,001,309.312	6156.45	4/8	NA/1	1/4	1/4
13	11,026,286.046	61,564.5	4/8	NA/2	1/3	1/4
14	11,760,377.223	61,564.5	5/8	2/2	NA/3	1/4
15	12,698,469.199	61,564.5	4/8	2/2	1/3	1/4
16	11,190,405.990	116,972.55	5/8	2/NA	NA/5	1/4
17	11,490,250.028	116,972.55	4/8	2/3	1/2	1/4
18	12,108,442.132	116,972.55	3/8	3/1	2/4	1/4
19	22,890,641.987	13,161.85	5/8	1/5	NA/NA	1/4
20	23,966,500.999	13,161.85	5/8	1/1	NA/4	1/4
21	26,483,466.466	13,161.85	5/8	1/1	NA/4	1/4
22	22,587,702.109	131,618.5	5/8	2/1	NA/4	1/4
23	23,460,743.447	131,618.5	3/8	2/NA	2/5	1/4
24	25,412,383.705	131,618.5	2/8	2/NA	3/5	1/4
25	22,171,657.968	250,075.15	4/8	2/NA	1/5	1/4
26	22,826,858.010	250,075.15	3/8	2/1	2/4	1/4
27	24,335,539.053	250,075.15	3/8	3/1	2/4	1/4

Table 5
Computational results of the stochastic optimization model.

	Total CLSC cost (Objective 1)	Total collection coverage (Objective 2)
Total number of variables	219,690	219,690
Total number of binary variables	23,209	23,209
Total number of constraints	230,501	230,501
Total number of iterations	222,436	72,119
Total cost of the CLSC	\$12,071,480	\$18,141,430
Total collection coverage	38,055.295 units	76,749.029
CPU time (s)	960	120
Number of opened regional wholesalers	4	8
Number of opened collection centers	1	–
Number of opened hybrid facilities	1	5
Number of opened licensed recycling facilities	1	4

Table 7
Triangular fuzzy numbers for the other possibilistic parameters.

Uncertain parameter	Triangular fuzzy number
Maximum numbers of opened collection centers & hybrid facilities (units)	(3, 5, 7)
Maximum allowable distances for forward flows (km.)	(400, 500, 600)
Maximum allowable distances for collection (km.)	(300, 400, 500)
Recycling rate for battery type 1	(70%, 80%, 95%)
Recycling rate for battery type 2	(60%, 70%, 80%)
Recycling rate for battery type 3	(65%, 75%, 85%)

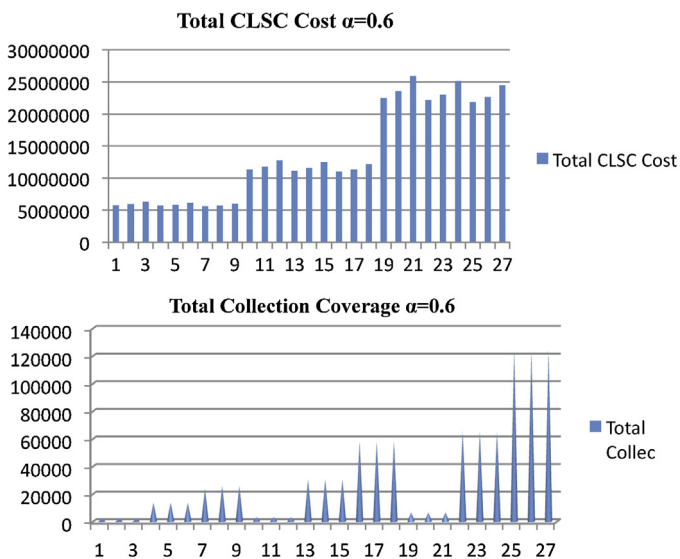
coverage is to lose the ability of opening more collection/hybrid facilities with more flexible allowable distances. Actually, the value of minimum acceptable feasibility degree can be varied based on the decision maker preferences. In other words, total expected CLSC cost and total expected collection coverage loses their importance when the decision maker decided to response to the different uncertainty categories (stochastic & epistemic) with a higher confidence level. Performance of the hybrid model for each objective under each scenario is displayed in Figs. 6 and 7 where the

Table 6
Fixed opening cost for the potential depots (regional wholesalers, collection centers and hybrid facilities).

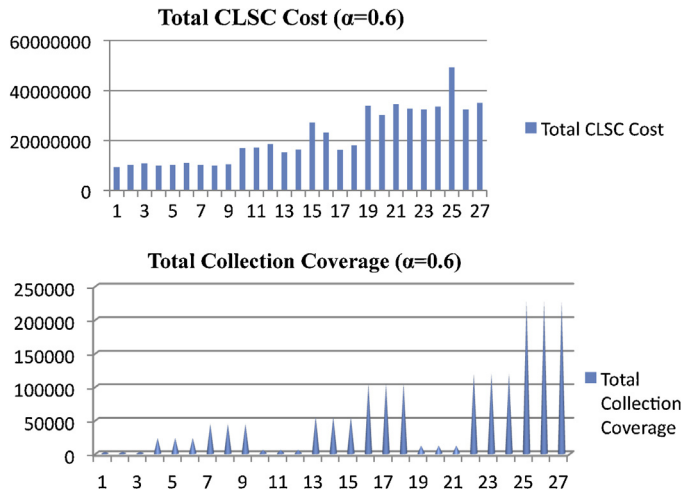
Location	Fixed cost of regional wholesalers (\$)	Fixed cost of collection centers (\$)	Fixed cost of hybrid facilities (\$)
Istanbul (1st region)	(150,000, 170,000, 180,000)	(50,000, 70,000, 100,000)	(220,000, 230,000, 260,000)
Istanbul (2nd region)	(160,000, 180,000, 210,000)	(70,000, 90,000, 120,000)	(270,000, 290,000, 320,000)
İzmir	(150,000, 170,000, 200,000)	(40,000, 60,000, 90,000)	(250,000, 270,000, 300,000)
Ankara	(140,000, 160,000, 190,000)	(80,000, 100,000, 130,000)	(230,000, 250,000, 280,000)
Eskişehir	(170,000, 190,000, 220,000)	(80,000, 100,000, 130,000)	(290,000, 310,000, 330,000)
Konya	(180,000, 200,000, 230,000)	(75,000, 95,000, 125,000)	(310,000, 330,000, 350,000)
Antalya	(210,000, 230,000, 260,000)	(100,000, 120,000, 150,000)	(270,000, 290,000, 310,000)
Gaziantep	(170,000, 190,000, 220,000)	(60,000, 80,000, 110,000)	(270,000, 290,000, 320,000)
Diyarbakır	(195,000, 215,000, 245,000)	(88,000, 108,000, 138,000)	(270,000, 290,000, 320,000)
Trabzon	(200,000, 220,000, 250,000)	(50,000, 70,000, 100,000)	(320,000, 340,000, 360,000)
Samsun	(210,000, 230,000, 260,000)	(70,000, 90,000, 120,000)	(370,000, 390,000, 420,000)
Kars	(170,000, 190,000, 220,000)	(75,000, 85,000, 115,000)	(250,000, 270,000, 300,000)
Manisa	(190,000, 210,000, 240,000)	(90,000, 110,000, 140,000)	(330,000, 350,000, 380,000)

Table 8
Summary of the results of hybrid model with different feasibility degrees.

	Total CLSC cost (Objective 1)	Total Collection Coverage (Objective 2)
α -level (0.6)		
Total cost of the CLSC	\$11,853,420	\$97,388,000
Total collection coverage	37,936.61 units	68,891.7 units
CPU time (s)	2235	120
Number of opened regional wholesalers	4	9
Number of opened collection centers	1	3
Number of opened hybrid facilities	1	1
Number of opened licensed recycling facilities	1	4
α -level (0.8)		
Total cost of the CLSC	\$11,910,436.68	\$18,599,440
Total collection coverage	38,055.3	68,891.7 units
CPU time (s)	2645	203
Number of opened regional wholesalers	3	9
Number of opened collection centers	1	NA
Number of opened hybrid facilities	1	4
Number of opened licensed recycling facilities	1	4
α -level (1.0)		
Total cost of the CLSC	\$11,969,920	\$1,515,178,000
Total collection coverage	38,055.3	62,240.63
CPU time (s)	3265	4367
Number of opened regional wholesalers	4	9
Number of opened collection centers	1	NA
Number of opened hybrid facilities	1	4
Number of opened licensed recycling facilities	1	4

**Fig. 6.** Computational results of the hybrid model for each scenario optimizing only total CLSC cost.

minimum acceptable feasibility degree is equal to 0.6. Figs. 6 and 7 show similar results with the stochastic optimization model's outcomes in terms of the effects of stochastic parameters changes. Corresponding optimal configurations of the hybrid model for the same feasibility degree ($\alpha=0.6$) are also presented in below Figs. 8 and 9. These figures are constructed for the scenario #13.

**Fig. 7.** Computational results of the hybrid model for each scenario optimizing only total collection coverage.

Note in Fig. 8 that recycled materials are only sent to the first battery manufacturer. Other manufacturer purchases the required materials from the vendors for new battery production.

In Fig. 9, in addition to battery purchasing from the scrap dealers, there are also battery sales to the scrap dealers.

In comparison of the deterministic, stochastic and the hybrid model in an aggregated manner, randomness in the data (stochastic parameters) yields to increasing in cost values. Fortunately, when the epistemic uncertainty in data is taken into account (hybrid model), total cost of the system decreases. Besides, when we handled different uncertainty categories in data, it is clear that total collection coverage increases. However, total amounts of collected batteries in the result of hybrid model are fewer compared to the stochastic optimization outcomes (see in Fig. 10).

5. Improvements on the current hybrid model via adapting risk management metrics

The previously formulated objectives of the proposed hybrid model are appropriate goals for the risk-neutral decision makers and do not take into account the risk management issues. However, the decision maker(s) of the CLSC network design problem may be a risk-averse person and want to manage the risks besides improving the total expected CLSC cost and total expected collection coverage simultaneously [1]. Moreover, it should be noted that when the CLSC network want to be designed under uncertainty (stochastic, possibilistic, fuzzy or hybrid of them), the financial risk and risk of collection related to the CLSC configuration should also be managed for providing useful managerial support to the decision makers. Therefore, additional objective(s) should be formulated or current objectives should be modified for managing these risks efficiently and effectively. In other words, this is required for obtaining a robust programming model which is able to take into consideration the decision maker(s)' favored risk aversion. In this study, four different risk measures such as Variability Index (VI), Downside Risk (DR) with deterministic & fuzzy targets and Conditional Value at Risk (CVaR) are applied and the results are compared. However, we did not use the variance management and probabilistic financial risk models due to the aforementioned disadvantages. In summary, different collection risk models besides financial risk distinct from the current literature are proposed for the first time in this paper.

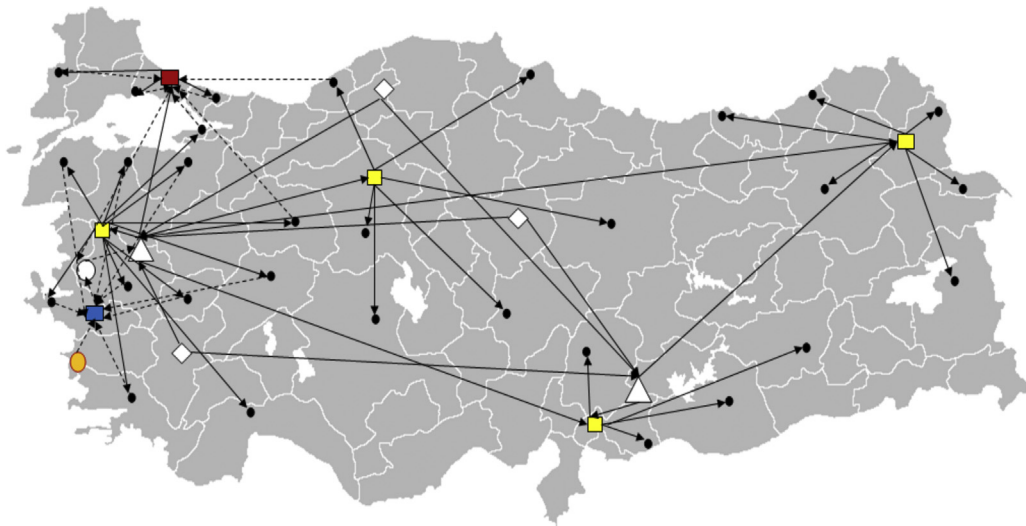


Fig. 8. Optimal CLSC network for hybrid model in scenario#13 considering only total cost ($\alpha = 0.6$).

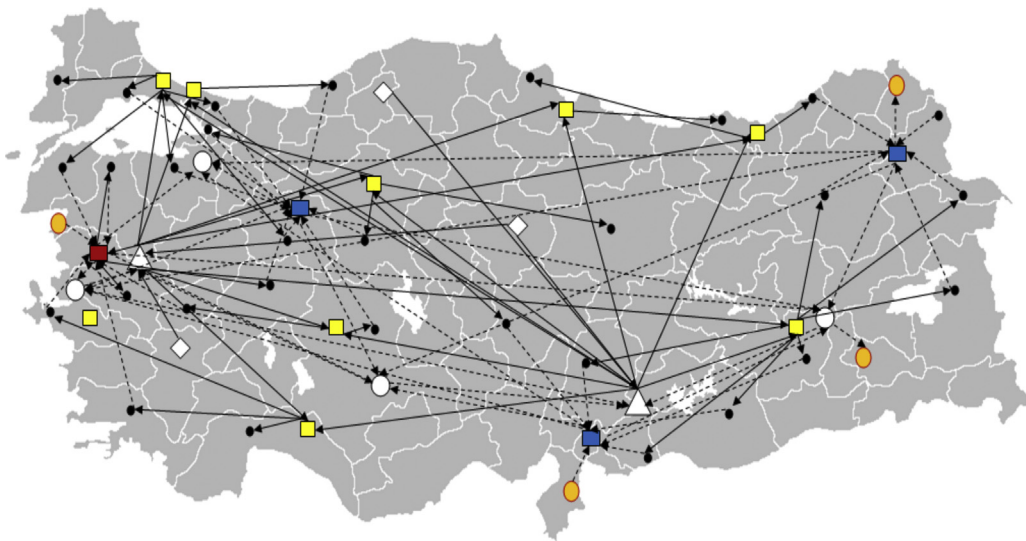


Fig. 9. Optimal CLSC network for hybrid model in scenario#13 considering only collection coverage ($\alpha = 0.6$).

5.1. Financial & collection variability index models (FVI & CVI)

Variability index model was defined by Ahmed and Sahinidis [33] as “the minimization of the positive deviation between the scenario costs and the expected cost”. If the scenario cost is greater than the expected cost, a non-negative auxiliary variable (Δ_s) is

introduced and equal to the positive difference between them, otherwise will be zero. Similarly for the collection coverage goal, another variable namely (β_s) is defined. If the scenario coverage is less than the expected collection coverage, this variable is equal to the positive difference between them, otherwise will also be zero. In this respect, FVI & CVI models are presented in Appendix

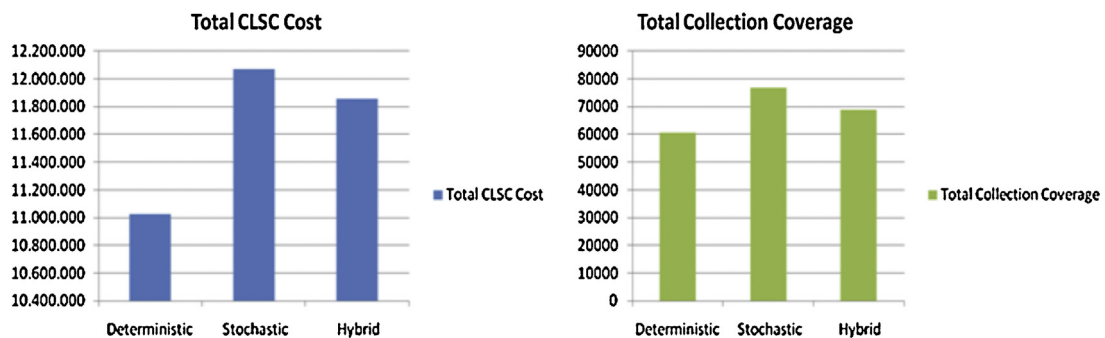


Fig. 10. Comparison of the results without risk management issues.

Table 9
Results for managing the financial variability index (FVI).

	$\alpha = 0.6$		$\alpha = 0.8$		$\alpha = 1.0$	
	$\rho = 0.8$	$\rho = 2.0$	$\rho = 0.8$	$\rho = 2.0$	$\rho = 0.8$	$\rho = 2.0$
Objective value (Minimizing the sum of expected cost and financial variability index) (\$)	13,562,269	16,624,264.28	13,630,000.12	16,460,002.79	1,370,754.66	16,296,994.83
Total expected CLSC cost (\$)	11,853,848.7	12,352,697.04	11,910,436.68	120,270,456.9	11,969,927.89	11,969,927.89
Total expected collection coverage (units)	37,898.9	38,055.3	38,055.3	41,656.16	38,055.3	38,055.3
Cost variability index (\$)	2,135,534.7	2,135,783.6	2,149,454.3	2,216,478.5	2,163,533.5	2,163,553.5
CPU time (s)	5548.5	4687.49	1153.03	46,758.97	66,125.3	15,225.5

IV. In these models, objective functions represent weighted sum between total expected CLSC cost/collection coverage and expected FVI & CVI, respectively. A trade off can be made between the total expected CLSC cost and the cost variability index (CVI) by using the different values of the weighted parameter. In this study, the weighted parameter is taken as 2.0 as in the study of You et al. [1]. Different from their study, another value that is close to zero ($\rho = 0.8$) is also considered. As can be expected, it is observed that when the value of this parameter approximates to zero, obtained total expected CLSC cost and/or collection coverage will gain similar values with the hybrid model results (before managing the variability index). Firstly, the FVI model is solved with all of the constraints in Section 3.1. Results for managing the FVI & CVI with different weighted parameters (ρ) and feasibility degrees (α) are given in Tables 9 and 10.

As it can be seen from these Tables 9 and 10, when more importance is given to FVI & CVI, (weight coefficient is increased), total expected CLSC cost will also increase and total expected collection coverage will decrease as a result of risk management. Similarly, when the feasibility degree of the constraints (α -level) is increased, total expected CLSC cost increases when more importance is given to the total expected CLSC cost ($\rho = 0.8$). However, when $\rho = 2.0$ or minimizing the FVI is determined as the mainly goal, total expected CLSC cost decreases.

For managing the CVI, when both weighted parameter and feasibility degree are increased, total expected coverage will decrease as an expected result. A detailed cost and coverage distributions before and after managing the financial and collection variability indexes are shown in Fig. A1 (for $\alpha = 0.6$ and $\rho = 2.0$) in Appendix V. Fig. A1 shows that after managing the financial variability index, percent of scenarios which are close to the total expected CLSC cost (\$11,853,420) increases. Additionally, after managing the CVI, percent of scenarios, which have more than 50,000 units of collection coverage for the spent batteries increases clearly.

5.2. Financial & collection downside risk with deterministic & fuzzy targets (FDR & CDR)

This risk measure provides lower probability of high cost or higher probability of low cost. Firstly, a positive deviation variable

(δ_s and/or θ_s) which represents the difference between predetermined target Ω and the scenario cost or coverage is introduced. If the scenario cost is less than the target value, this positive deviation is equal to zero. Otherwise, it will be equal to positive difference between them. Correspondingly, if the scenario collection coverage is greater than the target value, this positive deviation will be again equal to zero. Briefly, this risk measure contributes to objective functions under undesired circumstances. The formulations of the compact linear mathematical model for the financial & collection downside risks (FDR & CDR) with deterministic targets are given in Appendix VI. It should be noted that these risk values are not probabilities as in the probabilistic financial risk metric, they are described by the same units (\$ or units) with the goals.

Downside risk metric determines certain target values for the objectives. However, determination of these target values in a definite way or implicitly is generally a difficult task for the decision makers since the lack of some information or uncertainty. Therefore, these target values should be stated imprecisely and taken as fuzzy data. Therefore, proposed fuzzy version of the downside risk model can also be provided as in the Appendix VI. Before solving this fuzzy risk model, transformation process of Jimenez et al. [30] should be performed as mentioned in Section 3.2. It is worthwhile that the corresponding formulations in Appendix VI represent the transformed form of the fuzzy risk model into the crisp one. In the downside risk model with fuzzy targets, it is assumed that following triangular fuzzy numbers (\$11,000,000, \$12,500,000, \$15,000,000) and (40,000 units, 60,000 units, 70,000 units) are determined by the decision maker for the uncertain target values. In the downside risk model with deterministic targets, decision maker sets the most likely values of the above fuzzy triangular numbers (\$12,500,000 and 60,000 units) as the deterministic target values. When FDR and CDR are optimized separately with these deterministic and fuzzy targets, results given in Tables 11 and 12 are obtained.

Fig. 11 displays that managing the FDR provides more confidential solutions in terms of higher probability of low cost scenarios for the decision maker. When comparing FDR measures with deterministic and fuzzy targets, it is obviously seen from the same figure that they present very close consequences. However, it is very important that when the uncertainty of the target value is taken into account, percent of scenarios around the predetermined triangular fuzzy number increases.

Table 10
Results for managing the collection variability index (CVI).

	$\alpha = 0.6$		$\alpha = 0.8$		$\alpha = 1.0$	
	$\rho = 0.8$	$\rho = 2.0$	$\rho = 0.8$	$\rho = 2.0$	$\rho = 0.8$	$\rho = 2.0$
Objective value (maximizing the difference between expected coverage and collection variability index) (units)	52,174.32	31,800.36	52,174.33	31,800.36	47,506.31	29,183.97
Total expected CLSC cost (\$)	12,607,632.9	321,604,312.5	34,074,618.22	17,834,983.2	866,750,346.5	520,393,015
Total expected collection coverage (units)	68,891.7	55,061.9	68,891.7	55,062	62,240.63	51,125.5
Collection variability index (units)	20,896.7	11,630.8	20,896.72	11,630.8	18,417.9	10,970.7
CPU time (s)	145.7	6584.8	215.8	2961.8	681.1	33,390.2

Table 11
Results for managing the financial downside risk with deterministic & fuzzy targets (FDR).

	$\alpha = 0.6$		$\alpha = 0.8$		$\alpha = 1.0$	
	Deterministic	Fuzzy	Deterministic	Fuzzy	Deterministic	Fuzzy
Total expected CLSC cost (\$)	12,549,291.19	12,555,154.09	12,667,361.51	12,605,292.12	12,474,183.1	12,389,385.16
Total expected collection coverage (units)	20,552.5	20,555.9	20,881.89	22,447.3	20,436.2	23,563.2
Financial downside risk (\$)	1,993,428.75	1,983,303.75	2,018,705.44	2,119,953.51	2,060,527.6	2,242,730.44
CPU time (s)	6650.26	4810.55	3240.8	13,414.9	4182.1	2713.15

Table 12
Results for managing the collection downside risk with deterministic & fuzzy targets (CDR).

	$\alpha = 0.6$		$\alpha = 0.8$		$\alpha = 1.0$	
	Deterministic	Fuzzy	Deterministic	Fuzzy	Deterministic	Fuzzy
Total expected CLSC cost (\$)	18,026,767.4	683,085,107.6	203,844,543.2	18,179,531.6	18,120,409.28	18,183,304.2
Total expected collection coverage (units)	48,824.15	64,376.65	54,661.37	49,996.61	50,717.85	50,251.8
Collection downside risk (units)	14,939.28	14,269.27	14,939.28	16,279.27	16,916.67	20,266.67
CPU time (s)	81.1	538.92	114.5	72.15	65.23	92.17

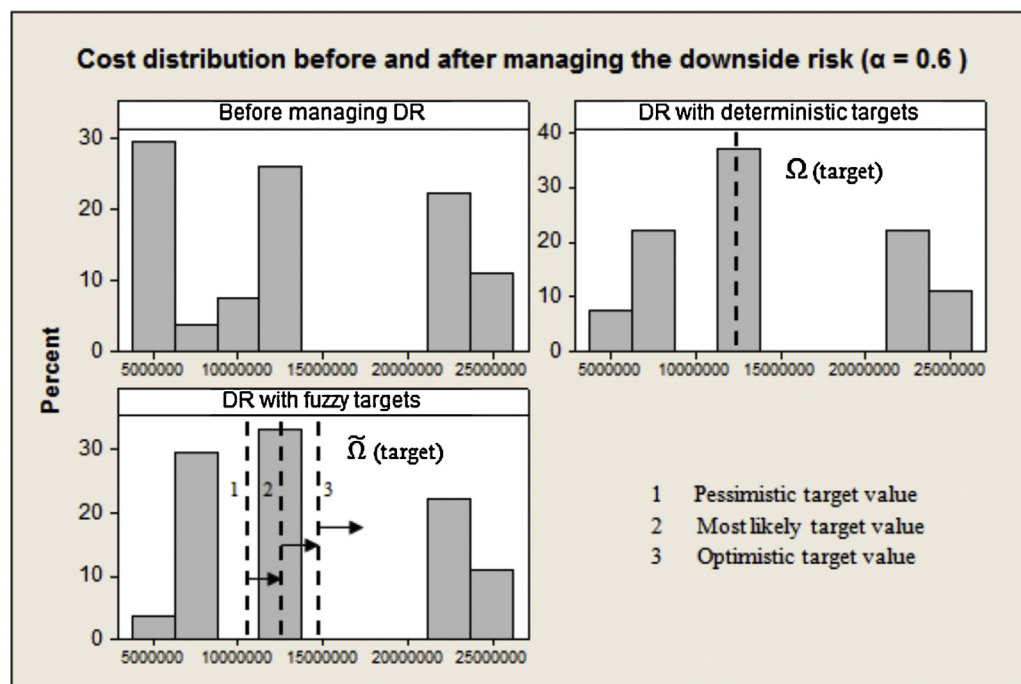
In addition, more promising results are obtained for both total expected CLSC cost (\$12,389,385.16) and total expected collection coverage (23,563.2 units) from the FDR measure with fuzzy target value when the feasibility degree of constraints is equal to 1.0.

As it can be seen from Table 12 and Fig. 12, managing only the collection downside risk, higher probability of high coverage scenarios, high total expected collection coverage (64,376.65 units) and less collection downside risk value (14,269.27 units) are provided in the case of fuzzy targets for $\alpha = 0.6$. However, when the feasibility degree of constraints is increased, higher total expected collection coverage value and less downside risk value are yielded in the case of deterministic targets (for $\alpha = 0.8$ and 1.0).

Summary of the results show that minimizing FDR causes lower collection coverage amounts. Similarly, optimizing CDR leads to higher costs and financial downside risk value.

5.3. Financial and collection conditional value at risk models (FCVaR and CCVaR)

Conditional value at risk (β -CVaR) is the conditional expectation of losses above the amount ∇ with probability β . The definitions ensure that the Value at Risk (β -VaR) is never more than β -CVaR. Therefore, low β -CVaR must have β -VaR as well [34]. In other words, CVaR is weighted average of VaR and CVaR⁺, where CVaR⁺ represents the “upper CVaR” or expected losses strictly exceeding VaR. Indeed, CVaR considers both probability and magnitude of loss. However, VaR takes only into account the probability of loss, not magnitude [35]. In other words, VaR only considers the extreme percentile of a gain/loss distribution without considering the magnitude of the loss. Therefore, a variant of VaR, namely CVaR has been widely utilized. Additionally, optimization process of CVaR can be

**Fig. 11.** Histogram of the cost distribution before and after managing the financial downside risk (FDR).

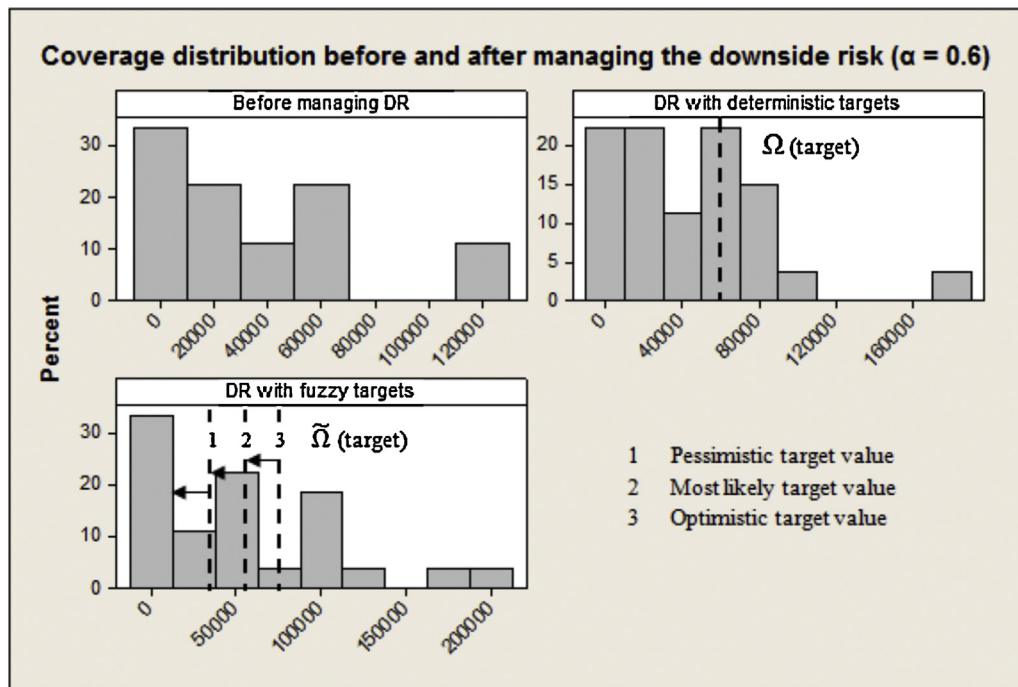


Fig. 12. Histogram of the coverage distribution before and after managing the collection downside risk (CDR).

Table 13
Results for managing the FCVaR model with different α -levels and weighting factors.

	$\alpha = 0.6$		$\alpha = 0.8$		$\alpha = 1.0$	
	$\gamma = 1.0$	$\gamma = 2.0$	$\gamma = 1.0$	$\gamma = 2.0$	$\gamma = 1.0$	$\gamma = 2.0$
Objective value (Minimizing the total expected cost with FCVaR) (\$)	15,441,048.64	18,801,063.99	15,527,522.76	18,874,617.15	15,506,190.99	18,965,892.1
Total expected CLSC cost (\$)	11,963,217.44	11,924,867.7	11,923,887.7	11,978,484.56	12,046,489.9	12,046,489.9
Total expected collection coverage (units)	14,351.4	14,351.4	21,663.27	14,351.4	11,443.8	11,443.82
CPU time (s)	45,099	12,998.72	1927.97	1141.5	2113.2	7778.8

Table 14
Results for managing the proposed CCVaR model with different α -levels and weighting factors.

	$\alpha = 0.6$		$\alpha = 0.8$		$\alpha = 1.0$	
	$\gamma = 1.0$	$\gamma = 2.0$	$\gamma = 1.0$	$\gamma = 2.0$	$\gamma = 1.0$	$\gamma = 2.0$
Objective value (Maximizing the total expected coverage with CCVaR) (\$)	57,328.68	46,343.55	57,328.68	46,343.81	51,504.27	41,304.1
Total expected CLSC cost (\$)	1,592,575,169.1	658,650,715.8	19,304,819.5	18,447,629.65	18,122,751.42	54,204,436.73
Total expected collection coverage (units)	68,568.9	66,475.3	68,593.3	66,725.3	61,781.36	59,152.8
CPU time (s)	796.3	2174.06	84.7	573.58	103.59	1379.78

very simple in computational issues [36]. It was also implied by Babazadeh et al. [5] that CVaR is a measurement of risk related to an investment focusing on the less profitable outcomes. In detail, β -CVaR can be defined as “minimization of the expected value of the costs in the $(1 - \beta) \times 100\%$ worst cases” [37]. Accounting the risks beyond VaR and measuring the downside risk are the most important features of CVaR [35]. In fact, CVaR aims to reduce probability a portfolio will incur large losses. In the light of the foregoing, mathematical model of the financial conditional value at risk (FCVaR) for our CLSC network design problem is presented in Appendix VII. The proposed CVaR for maximizing collection coverage (CCVaR) is also given in the same appendix.

Differently from the FCVaR, positive deviation between the VaR and loss function is computed in the CCVaR. When the FCVaR

& CCVaR are optimized separately with different degree of feasibility and weighting factor values, the following results given Tables 13 and 14 are obtained. Results of the FCVaR & CCVaR models show that minimizing total expected CLSC Cost with FCVaR causes low collection coverage. In contrast, optimizing total expected collection coverage with CCVaR leads to high total expected CLSC costs. Moreover, increments in the feasibility degree and weighting factor cause escalation in the related performance measures as a result of the risk management.

According to Table 13, as a result of risk management total expected CLSC cost increases as the feasibility degree of constraints is increased. However, as it can be seen from Appendix VIII (see in Fig. A2) that significant improvements in financial risks, especially in terms of the cost distribution may not be provided by increasing

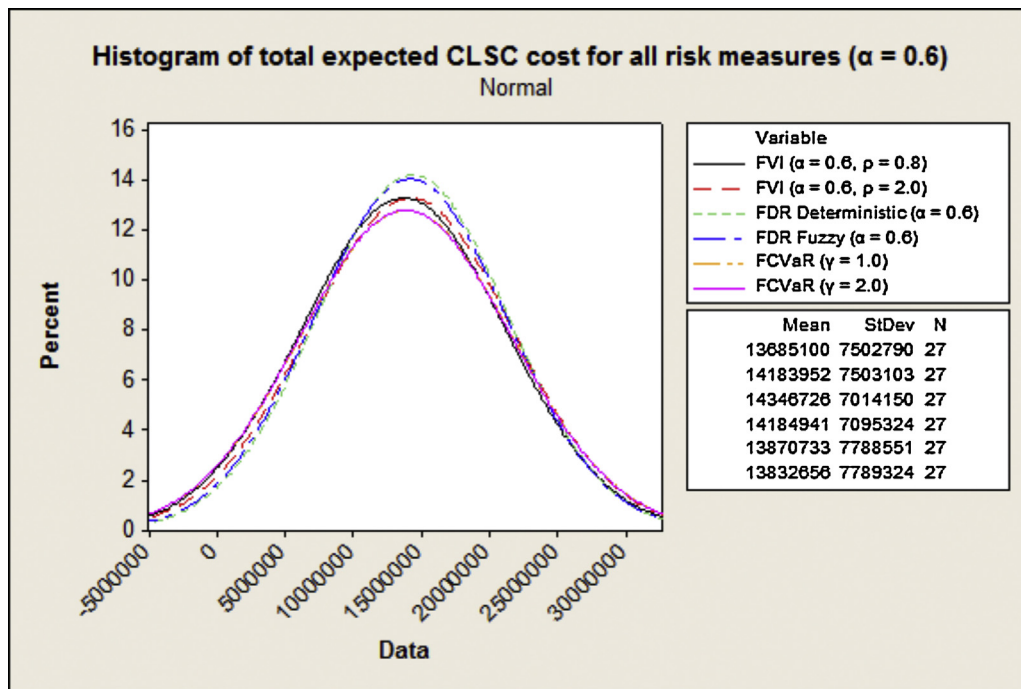


Fig. 13. Histogram of the normally distributed scenario costs for each risk measure.

the weighting factor. Fortunately, slightly larger percent of low cost scenarios are obtained.

Similar results are acquired after managing the collection risks with CCVaR measure. One can see from Table 14 that total expected collection coverage decreases in the case of simultaneous increasing in both feasibility degree and weighting factor. As a result, using the given data in this study it is found that CVaR measure has not an important effect on decreasing the percentage of high cost and low coverage scenarios as it can be seen from Appendix VIII (see in Figs. A2 and A3).

Thus, comparison of CVaR with the other risk measures which was scheduled as a future work by Babazadeh et al. [5] is carried out in this section. Moreover, one can see a detailed comparison for both financial & collection risk measures in Figs. 13 and 14. When the results of all the risk measures are evaluated in terms of financial risk of the CLSC, it is clearly seen from Fig. 11 that although downside risk measure with fuzzy targets presents higher means for the total cost, this risk measure has the lowest standard deviation. In addition, it was also previously demonstrated by Fig. 11 that the percentage of high cost scenarios in downside risk model

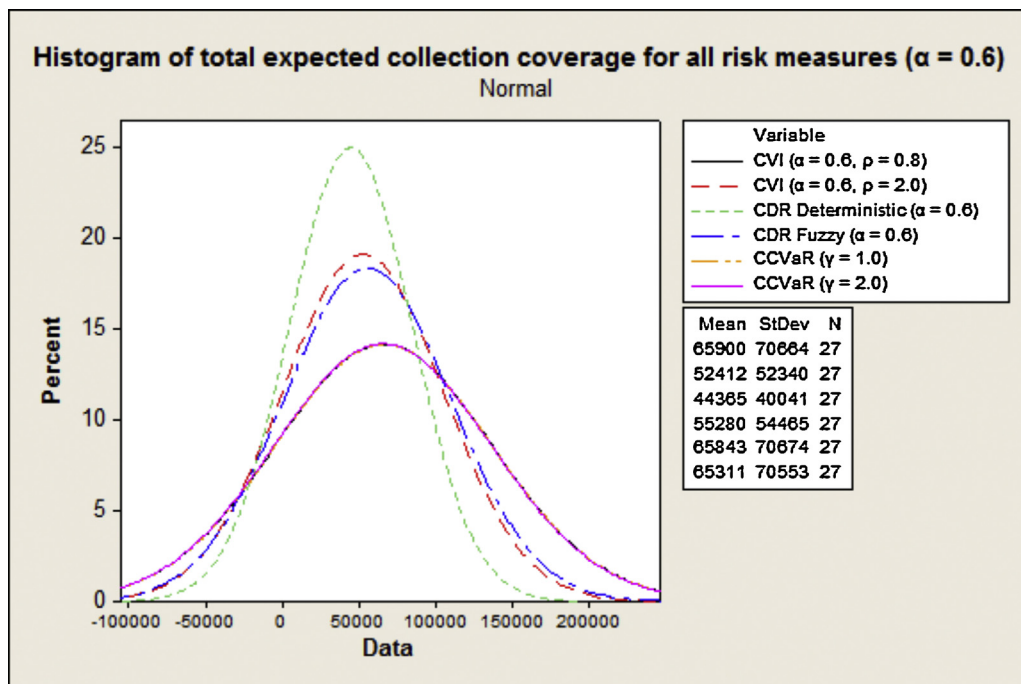


Fig. 14. Histogram of the normally distributed scenario coverage for each risk measure.

with fuzzy targets becomes sparse compared to other risk measures.

According to Fig. 14, downside risk with deterministic target has the lowest standard deviation for collection coverage. However, this risk measure has also the lowest coverage mean which is an undesirable situation. Therefore, downside risk measure with fuzzy target or collection variability index ($\alpha=0.6$, $\rho=2.0$) can be used by the decision maker(s) for higher levels of coverage mean and acceptable degree of standard deviation. Moreover, percent of high coverage scenarios in DR with fuzzy target is found to be greater compared to variability index measure.

In summary, a robust programming approach which can consider the attitude of decision maker(s) toward risk is provided by adapting different risk management metrics. It can be seen from the cost and coverage distributions of different scenarios as depicted from Figs. 12, 13 and A1–A3 that significant improvements can be provided in terms of increasing percent of low cost scenarios and high coverage scenarios after managing risks. This can be the best achieved by the proposed downside risk models with fuzzy targets which present lowest standard deviation for the financial risks and highest level of coverage mean with acceptable degree of standard deviation.

6. Conclusion and future researches

In this study, a new multi-objective, multi-echelon, multi-product CLSC network design model is developed for a lead/acid battery industry considering both financial and collection risks using several risk measures under different uncertainty types. It should be underlined that before managing the risks along the CLSC, one should pay attention to the uncertainty related to the handled problem effectively. In addition, different uncertainty types might occur in most of the real life cases. For this reason, this paper presents a hybrid scenario based stochastic & possibilistic programming approach to CLSC network design for a better reflection of real life applications. After handling different uncertainty types simultaneously, most commonly used risk measures in the literature are integrated into the proposed hybrid model. Apart from the available literature, these existing risk measures are revised for the collection coverage objective. Particularly for the downside risk, target value which is determined by the decision maker(s) is considered as uncertain and represented by triangular fuzzy numbers as the values for these parameters contain some sort of ambiguity. Summary of the results show that total expected CLSC cost increases and total expected collection coverage decreases after risk management. Furthermore, outcomes of the different risk measures suggest that using downside risk with fuzzy targets will be the best choice in terms of both computational efficiency, handling uncertainty and solution quality. For the future works, Pareto optimal solutions can be found by applying a multi-objective optimization methodology by considering total expected CLSC cost, collection coverage goals simultaneously with their risk issues. Additionally, a novel risk measure which focuses on both variability and targets or losses may also be scheduled as a future research.

Appendix I.

Compact form of the proposed hybrid mathematical model:

$$OF1 = \text{Min} \tilde{f} \cdot y + \sum_{s \in S} \pi_s \cdot \beta_s \cdot \tilde{\alpha} \cdot x_s$$

$$OF2 = \text{Max} \sum_{s \in S} \pi_s \cdot c_s \cdot y''_s$$

Subject to;

$$a \cdot x_s \leq b$$

$$c_s \cdot x_s = d_s$$

$$y \leq \tilde{e}$$

$$g \cdot y''_s = \tilde{h}$$

$$x_s = \tilde{k}$$

In the above formulation, $\tilde{f}$ and $\tilde{\alpha}$ correspond to possibilistic cost parameters, $\tilde{e}$, $\tilde{h}$, $\tilde{k}$ and d_s represent possibilistic and stochastic right hand sides, respectively. b and g correspond to deterministic coefficients. y displays binary variables independent from the scenarios. On the other hand, y''_s are also binary variables for each scenario s . The continuous variables x_s correspond to the flows between the CLSC stages for each scenario.

Appendix II. Nomenclature

Indices and sets

b	set of battery type $b \in B$
c	set of component type $c \in C$
i	set of new battery manufacturers $i \in I$
j	set of potential depots such as regional wholesalers, collection centers or hybrid facilities $j \in J$
k	set of battery dealers, retailers or authorized automotive services $k \in K$
l	set of potential licensed recycling facilities $l \in L$
v	set of vendors $v \in V$
s	set of potential scenarios $s \in S$

Model parameters

Stochastic parameters

DE_{bks}	demand of battery dealer or retailer k for battery type- b in scenario s
S_{bs}	returned fraction of demand for battery type- b from battery dealers or retailers in scenario s
θ_{bs}	disposal rate for battery type- b over scenario s (ratio for inappropriate condition of batteries for recycling)
π_s	occurrence probability of scenario s

Possibilistic parameters

$\tilde{f}_1$	opening cost of the regional wholesaler j
$\tilde{f}_2$	opening cost of the collection center j
$\tilde{f}_3$	opening cost of the hybrid facility j
$\tilde{f}_4$	opening cost of the licensed recycling facility l
$\widetilde{PRC}_b$	production cost of one unit of battery type- b in each new battery manufacturer
$\widetilde{TC}_b$	transportation cost of one unit of battery type- b per kilometer
$\widetilde{TC1}_b$	transportation cost of one unit of used battery type- b per kilometer
$\widetilde{TC}_c$	transportation cost of material/component type- c in kilograms per kilometer
$\widetilde{PUC}_{cvi}$	purchasing cost of material/component type- c in kilograms from vendor v for manufacturer i
$\widetilde{PC}_{bj}$	purchasing cost of one unit of used battery type- b from any scrap dealer for depot j
$\widetilde{SP}_{bj}$	selling price of one unit of used battery type- b from depot j to any scrap dealer
$\widetilde{RC}_{bl}$	recycling cost per unit of used battery type- b in licensed recycling facility l
$\widetilde{CC}_b$	collection cost per unit of spent battery type- b

$\widetilde{DIC}_b$	disposal cost per unit of un-recyclable battery type- b	$d4_{li}$	the distance between licensed recycling facility l and new battery manufacturer i
$\widetilde{\gamma}_b$	recycling rate for battery type- b	M	an arbitrary set large number
$\widetilde{N}$	maximum number of opened collection centers and hybrid facilities		
$\widetilde{DMAX}$	maximum allowable distance from a given regional wholesaler or hybrid facility to a battery dealer or retailer for new battery distribution	Decision variables	
$\widetilde{D1MAX}$	maximum allowable distance from a given battery dealer or retailer to a collection center or hybrid facility for used battery collection	w_j	1, if a regional wholesaler is opened at location j ; 0, otherwise
Deterministic parameters		c_j	1, if a collection center is opened at location j ; 0, otherwise
W_b	weight of the used battery type- b	h_j	1, if a hybrid facility is opened at location j ; 0, otherwise
ε_{cb}	percentage of contribution of material/component type- c for the used battery type- b	r_l	1, if a licensed recycling facility is opened at location l ; 0, otherwise
ρ_{cb}	amount of material/component type- c to produce one unit of new battery type- b	Q_{bis}	production quantity of battery type- b for new battery manufacturer i in scenario s
α_{jk}	binary parameter is equal to 1, if the distance between the battery dealer k and collection center or hybrid facility j is within the maximum acceptable distance. 0, otherwise	x_{bijks}	quantity of battery type- b shipped from new battery manufacturer i via regional wholesaler or hybrid facility j to the battery dealer k in scenario s
cap_{bj}^f	capacity of regional wholesaler j for forward flows of newly produced battery type- b	$x1_{bkjls}$	quantity of used battery type- b shipped from battery dealer k via collection center j or hybrid facility j to the licensed recycling facility l in scenario s
$hcap_{bj}^f$	capacity of hybrid facility j for forward flows of newly produced battery type- b	$x2_{clis}$	quantity of material/component type- c shipped to new battery manufacturer i from licensed recycling facility l in scenario s
cap_{bj}^r	capacity of collection center j for reverse flows of spent battery type- b	QP_{cvis}	amount of material/component type- c purchased from vendor v by new battery manufacturer i in scenario s
$hcap_{bj}^r$	capacity of hybrid facility j for reverse flows of spent battery type- b	q_{bjls}	quantity of used battery type- b purchased by depot j (Hybrid facility or collection center) from any scrap dealer and sent to the licensed recycling facility l in scenario s
$Prcap_{bi}$	production capacity of new battery manufacturer i for battery type- b	$q1_{bjs}$	quantity of used battery type- b sold to any scrap dealer from depot j in scenario s
$REcap_{bl}$	recycling capacity of licensed recycling facility l for used battery type- b	RE_{bls}	recycling quantity of used battery type- b at licensed recycling facility l in scenario s
$Vcap_{cv}$	supply capacity of vendor v for material/component type- c	y_{jks}	1, if regional wholesaler or hybrid facility j serves battery dealer k for meeting its demand in the forward chain in scenario s ; 0, otherwise
$d1_{ij}$	the distance between new battery manufacturer i and depot j	$y1_{kjs}$	1, if collection center or hybrid facility j serves battery dealer k for collecting the returned batteries from this battery dealer in the reverse chain in scenario s ; 0, otherwise
$d2_{jk}$	the distance between depot j and battery dealer or retailer k	y_{bjs}	1, if depot j purchases used battery type- b from any scrap dealer in scenario s ; 0, otherwise
$d3_{jl}$	the distance between depot j and licensed recycling facility l	$y1_{bjs}$	1, if depot j sells used battery type- b to any scrap dealer in scenario s ; 0, otherwise

Appendix III.

The equivalent crisp α -parametric linear program:

$$\begin{aligned}
 E[\text{Total CLSC Cost}] = & \sum_{j \in J} \left(\frac{f1_j^{pes} + 2 \cdot f1_j^{mos} + f1_j^{opt}}{4} \right) \cdot w_j + \sum_{j \in J} \left(\frac{f2_j^{pes} + 2 \cdot f2_j^{mos} + f2_j^{opt}}{4} \right) \cdot c_j + \sum_{j \in J} \left(\frac{f3_j^{pes} + 2 \cdot f3_j^{mos} + f3_j^{opt}}{4} \right) \cdot h_j \\
 & + \sum_{l \in L} \left(\frac{f4_l^{pes} + 2 \cdot f4_l^{mos} + f4_l^{opt}}{4} \right) \cdot r_l + \sum_{b \in B} \sum_{i \in I} \sum_{s \in S} \pi_s \cdot Q_{bis} \cdot \left(\frac{PRC_b^{pes} + 2 \cdot PRC_b^{mos} + PRC_b^{opt}}{4} \right) \\
 & + \sum_{b \in B} \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \sum_{s \in S} \pi_s \cdot x_{bijk} \cdot \left(\frac{TC_b^{pes} + 2 \cdot TC_b^{mos} + TC_b^{opt}}{4} \right) \cdot (d1_{ij} + d2_{jk}) \\
 & + \sum_{b \in B} \sum_{l \in L} \sum_{s \in S} \pi_s \cdot RE_{bls} \cdot \left(\frac{RC_{bl}^{pes} + 2 \cdot RC_{bl}^{mos} + RC_{bl}^{opt}}{4} \right) + \sum_{b \in B} \sum_{k \in K} \sum_{j \in J} \sum_{l \in L} \sum_{s \in S} \pi_s \cdot x1_{bkjls} \cdot \left(\frac{TC1_b^{pes} + 2 \cdot TC1_b^{mos} + TC1_b^{opt}}{4} \right) \\
 & \cdot (d2_{jk} + d3_{jl}) + \sum_{c \in C} \sum_{l \in L} \sum_{i \in I} \sum_{s \in S} \pi_s \cdot x2_{clis} \cdot \left(\frac{TC_c^{pes} + 2 \cdot TC_c^{mos} + TC_c^{opt}}{4} \right) \cdot d4_{li} + \sum_{b \in B} \sum_{j \in J} \sum_{l \in L} \sum_{s \in S} \pi_s \cdot q_{bjls} \\
 & \cdot \left(\frac{TC1_b^{pes} + 2 \cdot TC1_b^{mos} + TC1_b^{opt}}{4} \right) \cdot d3_{jl} + \sum_{c \in C} \sum_{v \in V} \sum_{i \in I} \sum_{s \in S} \pi_s \cdot QP_{cvsi} \cdot \left(\frac{PUC_{cvi}^{pes} + 2 \cdot PUC_{cvi}^{mos} + PUC_{cvi}^{opt}}{4} \right) \\
 & + \sum_{b \in B} \sum_{j \in J} \sum_{l \in L} \sum_{s \in S} \pi_s \cdot q_{bjls} \cdot \left(\frac{PC_{bj}^{pes} + 2 \cdot PC_{bj}^{mos} + PC_{bj}^{opt}}{4} \right) + \sum_{b \in B} \sum_{j \in J} \sum_{k \in K} \sum_{s \in S} \pi_s \cdot y1_{kjs} \cdot DE_{bks} S_{bs} \\
 & \cdot \left(\frac{CC_b^{pes} + 2 \cdot CC_b^{mos} + CC_b^{opt}}{4} \right) - \sum_{b \in B} \sum_{j \in J} \sum_{s \in S} \pi_s \cdot q1_{bjs} \cdot \left(\frac{SP_{bj}^{pes} + 2 \cdot SP_{bj}^{mos} + SP_{bj}^{opt}}{4} \right) +
 \end{aligned}$$

$$\sum_{b \in B} \sum_{k \in K} \sum_{j \in J} \sum_{l \in L} \sum_{s \in S} \pi_s \cdot (x1_{bkjls} + q_{bjls} - q1_{bjs}) \cdot \theta_{bs} \cdot \left(\frac{DIC_b^{pes} + 2 \cdot DIC_b^{mos} + DIC_b^{opt}}{4} \right) (1^*)$$

$$\sum_{j \in J} c_j + h_j \leq \alpha \cdot \left(\frac{N^{pes} + N^{mos}}{2} \right) + (1 - \alpha) \cdot \left(\frac{N^{mos} + N^{opt}}{2} \right) \quad \forall S(3^*)$$

$$\sum_{i \in I} x2_{clis} \geq \sum_{b \in B} RE_{bls} \cdot \varepsilon_{cb} \cdot \left[\frac{\alpha}{2} \cdot \left(\frac{\gamma_b^{mos} + \gamma_b^{opt}}{2} \right) + \left(1 - \frac{\alpha}{2} \right) \cdot \left(\frac{\gamma_b^{pes} + \gamma_b^{mos}}{2} \right) \right] \quad \forall c, \forall l, \forall s(16^*)$$

$$\sum_{i \in I} x2_{clis} \geq \sum_{b \in B} RE_{bls} \cdot \varepsilon_{cb} \cdot \left[\frac{\alpha}{2} \cdot \left(\frac{\gamma_b^{pes} + \gamma_b^{mos}}{2} \right) + \left(1 - \frac{\alpha}{2} \right) \cdot \left(\frac{\gamma_b^{mos} + \gamma_b^{opt}}{2} \right) \right] \quad \forall c, \forall l, \forall s(16^{**})$$

$$d2_{jk} \cdot y_{jks} \leq \alpha \cdot \left(\frac{DMAX^{pes} + DMAX^{mos}}{2} \right) + (1 - \alpha) \cdot \left(\frac{DMAX^{mos} + DMAX^{opt}}{2} \right) \quad \forall j, \forall k, \forall s(20^*)$$

$$d2_{jk} \cdot y1_{kjs} \leq \alpha \cdot \left(\frac{D1MAX^{pes} + D1MAX^{mos}}{2} \right) + (1 - \alpha) \cdot \left(\frac{D1MAX^{mos} + D1MAX^{opt}}{2} \right) \quad \forall j, \forall k, \forall s(21^*)$$

where α is a parameter indicates the feasibility degree of constraints.

Appendix IV.

Financial and collection variability index models:

$$\text{Minimize } E[\text{Total CLSC Cost}] + \rho \cdot \sum_s \pi_s \cdot \Delta_s$$

$$\Delta_s \geq \text{Cost}_s - \left(\sum_s \pi_s \cdot \text{Cost}_s \right) \quad (27)$$

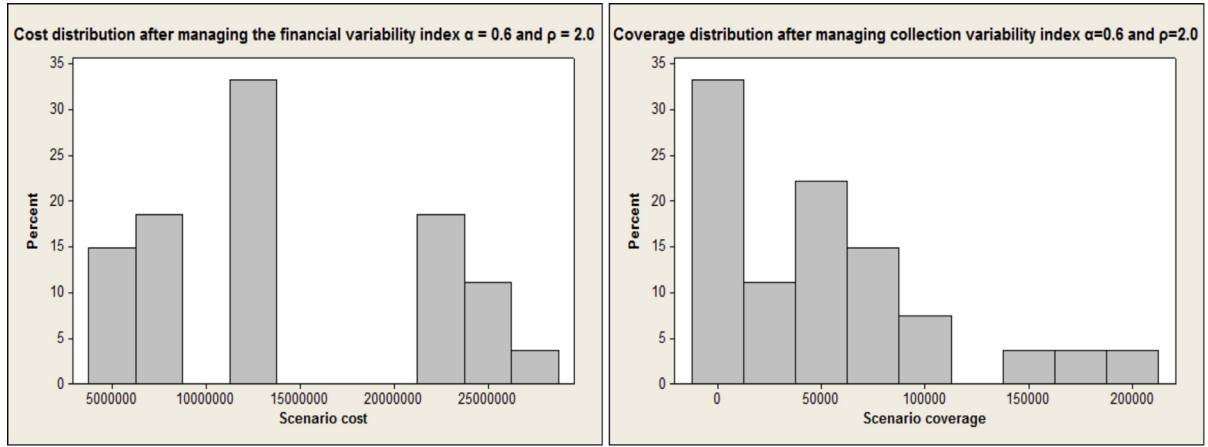


Fig. A1. Histogram of the cost and coverage distribution after managing the financial and collection variability indexes (FVI and CVI).

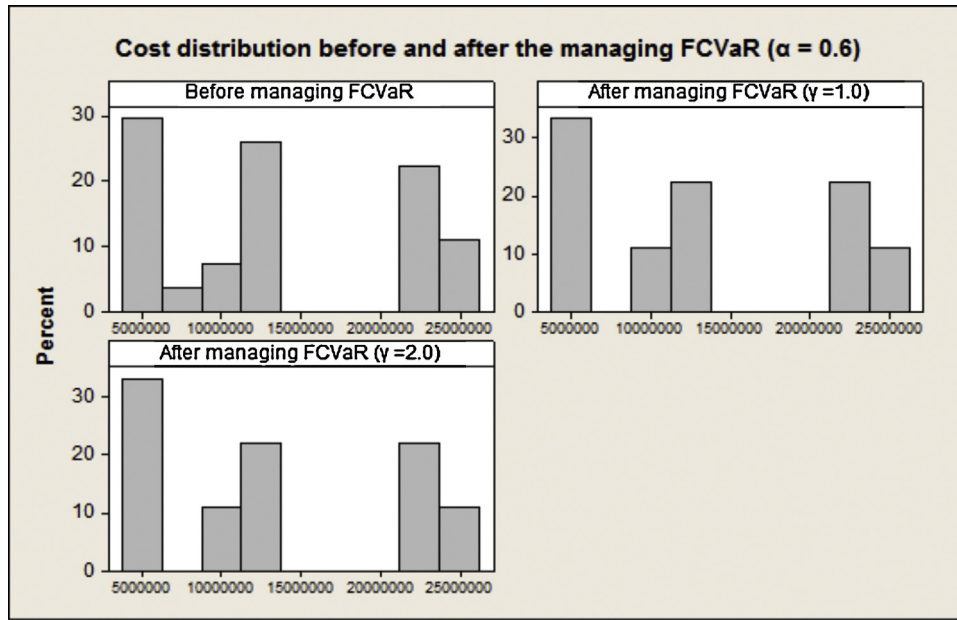


Fig. A2. Histogram of the cost distribution before & after managing financial conditional value at risk (FCVaR).

Constraint set (3)–(26) and $\Delta_s \geq 0 \quad \forall s \in S$

Minimize $E[\text{Total Collection Coverage}_s] + \rho \cdot \sum_{s \in S} \pi_s \cdot \beta_s$

$$\beta_s \geq \left(\sum_{s \in S} \pi_s \cdot \text{Coverage}_s \right) - \text{Coverage}_s \quad (28)$$

Constraint set (3)–(26) and $\beta_s \geq 0 \quad \forall s \in S$

where ρ is the weighted parameter.

Appendix V.

Cost and coverage distributions after utilizing variability index models are given in Fig. A1.

Appendix VI.

Downside risk models with deterministic targets:

$$\text{Minimize } \text{DRisk}(x, \Omega) = \sum_{s \in S} \pi_s \cdot \delta_s \quad (29)$$

$$\delta_s \geq \text{Cost}_s - \Omega$$

Constraint set (3)–(26) and $\delta_s \geq 0 \quad \forall s \in S$

$$\text{Minimize } \text{DRisk}(x, \Omega) = \sum_{s \in S} \pi_s \cdot \theta_s \quad (30)$$

$$\theta_s \geq \Omega - \text{Coverage}_s$$

Constraint set (3)–(26) and $\theta_s \geq 0 \quad \forall s \in S$

Downside risk models with fuzzy targets:

$$\text{Minimize } \text{DRisk}(x, \tilde{\Omega}) = \sum_{s \in S} \pi_s \cdot \delta_s \quad (31)$$

$$\delta_s \geq \text{Cost}_s - \left\{ \frac{\alpha \cdot (\Omega_{pes} + \Omega_{mos})}{2} + \frac{(1 - \alpha) \cdot (\Omega_{mos} + \Omega_{opt})}{2} \right\}$$

Constraint set (3)–(26) and $\delta_s \geq 0 \quad \forall s \in S$

$$\begin{aligned} \text{Minimize DRisk}(x, \tilde{\Omega}) &= \sum_{s \in S} \pi_s \cdot \theta_s \\ \theta_s &\geq \left\{ \frac{\alpha \cdot (\Omega_{mos} + \Omega_{opt})}{2} + \frac{(1 - \alpha) \cdot (\Omega_{pes} + \Omega_{mos})}{2} \right\} - \text{Coverage}_s \end{aligned} \quad (32)$$

Constraint set (3)–(26) and $\theta_s \geq 0 \quad \forall s \in S$

Appendix VII.

Mathematical formulations of the collection and financial conditional value at risk models:

$$\text{Minimize } E[\text{Total CLSC Cost}] + \gamma \cdot \left(\nabla + \left(\frac{1}{1 - \beta} \right) \cdot \sum_s \pi_s \cdot \varphi_s \right)$$

Subject to:

$$\begin{aligned} &\sum_j \left(\frac{f1_j^{pes} + 2.f1_j^{mos} + f1_j^{opt}}{4} \right) \cdot w_j + \sum_j \left(\frac{f2_j^{pes} + 2.f2_j^{mos} + f2_j^{opt}}{4} \right) \cdot c_j + \sum_j \left(\frac{f3_j^{pes} + 2.f3_j^{mos} + f3_j^{opt}}{4} \right) \cdot h_j \\ &+ \sum_l \left(\frac{f4_l^{pes} + 2.f4_l^{mos} + f4_l^{opt}}{4} \right) \cdot r_l + \sum_b \sum_i \sum_j \sum_k \pi_s \cdot x_{bijks} \cdot \left(\frac{TC_b^{pes} + 2.TC_b^{mos} + TC_b^{opt}}{4} \right) \cdot (d1_{ij} + d2_{jk}) \\ &+ \sum_b \sum_k \sum_j \sum_l \pi_s \cdot x1_{bkjls} \cdot \left(\frac{TC1_b^{pes} + 2.TC1_b^{mos} + TC1_b^{opt}}{4} \right) \cdot (d2_{jk} + d3_{jl}) + \sum_b \sum_j \sum_k \pi_s \cdot y1_{kjs} \cdot DE_{bks} \cdot S_{bs} \cdot \left(\frac{CC_b^{pes} + 2.CC_b^{mos} + CC_b^{opt}}{4} \right) \\ &+ \sum_b \sum_i \pi_s \cdot Q_{bis} \cdot \left(\frac{PRC_b^{pes} + 2.PRC_b^{mos} + PRC_b^{opt}}{4} \right) + \sum_b \sum_j \sum_l \pi_s \cdot q_{bjls} \cdot \left(\frac{TC1_b^{pes} + 2.TC1_b^{mos} + TC1_b^{opt}}{4} \right) \cdot d3_{jl} \\ &+ \sum_b \sum_j \sum_l \pi_s \cdot q_{bjls} \cdot \left(\frac{PC_{bj}^{pes} + 2.PC_{bj}^{mos} + PC_{bj}^{opt}}{4} \right) + \sum_c \sum_l \sum_i \pi_s \cdot x2_{clis} \cdot \left(\frac{TC_c^{pes} + 2.TC_c^{mos} + TC_c^{opt}}{4} \right) \cdot d4_{li} \\ &+ \sum_b \sum_l \pi_s \cdot RE_{bls} \cdot \left(\frac{RC_{bl}^{pes} + 2.RC_{bl}^{mos} + RC_{bl}^{opt}}{4} \right) + \sum_c \sum_v \sum_i \pi_s \cdot QP_{cvis} \cdot \left(\frac{PUC_{cvi}^{pes} + 2.PUC_{cvi}^{mos} + PUC_{cvi}^{opt}}{4} \right) \\ &+ \sum_b \sum_k \sum_j \sum_l \pi_s \cdot (x1_{bkjls} + q_{bjls} - q1_{bjs}) \cdot \theta_{bs} \cdot \left(\frac{DIC_b^{pes} + 2.DIC_b^{mos} + DIC_b^{opt}}{4} \right) \\ &- \sum_b \sum_j \pi_s \cdot q1_{bjs} \cdot \left(\frac{SP_{bj}^{pes} + 2.SP_{bj}^{mos} + SP_{bj}^{opt}}{4} \right) - \nabla - \varphi_s \leq 0 \quad \text{and} \quad \nabla, \varphi_s \geq 0 \quad \forall s \in S \end{aligned} \quad (33)$$

$$\begin{aligned} \text{Maximize } E[\text{Total Collection Coverage}] - \gamma \cdot \left(\nabla + \left(\frac{1}{1 - \beta} \right) \cdot \sum_s \pi_s \cdot \varphi_s \right) \\ \text{Subject to;} \end{aligned} \quad (34)$$

$$\nabla - \varphi_s - \sum_b \sum_k \sum_j \pi_s \cdot DE_{bks} \cdot S_{bs} \cdot y1_{kjs} \geq 0$$

Constraint set (3)–(26) and $\nabla, \varphi_s \geq 0 \quad \forall s \in S$

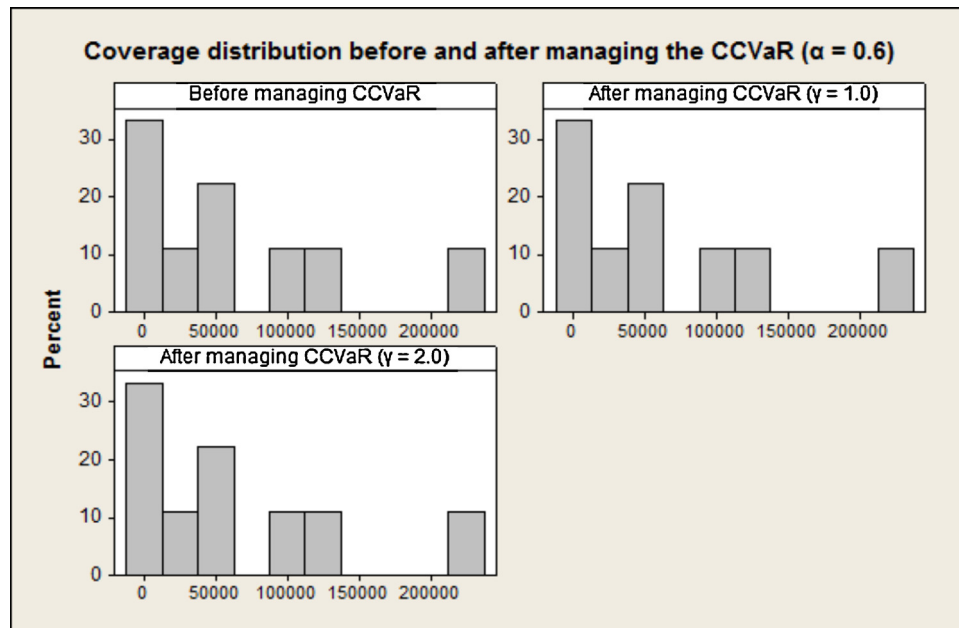


Fig. A3. Histogram of coverage distribution before & after managing collection conditional value at risk (CCVaR).

where φ_s represents the maximum difference between the loss function and ∇ for a particular scenario s . β is a specific confidence level and also taken as 95%. In addition, weighting factor γ is taken as 1.0 and 2.0 as in the study of Babazadeh et al. [5], respectively for each risk measure (FCVaR & CCVaR) in all of the computations. In the optimal solution, ∇ corresponds to the β -VaR.

Appendix VIII.

Cost and coverage distributions before and after utilizing conditional value at risk models are given in Figs. A2 and A3.

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